# Using Image Processing and Deep-Learning to Explore Digitized Historical Documents

A COLLABORATORY BETWEEN THE LIBRARY OF CONGRESS AND THE IMAGE ANALYSIS FOR ARCHIVAL DISCOVERY (AIDA) LAB AT THE UNIVERSITY OF NEBRASKA, LINCOLN, NE

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# Overview

- Part 1: Aida Project: Poem Recognition
  - Part 1.1: Segmentation
  - Part 1.2: Recognition
- Part 2: Document Image Quality Assessment (DIQA)
- Part 3: Zoning
- Part 4: Deep Learning
- Part 5: Five Collaboratory Projects with Library of Congress

# **AIDA** | Objective

❑ **Exploring what more we can do with the millions of images that represent the digitized cultural record—particularly digital images of textual materials—and we are interested in the types of discovery that serious attention to digital images might yield**

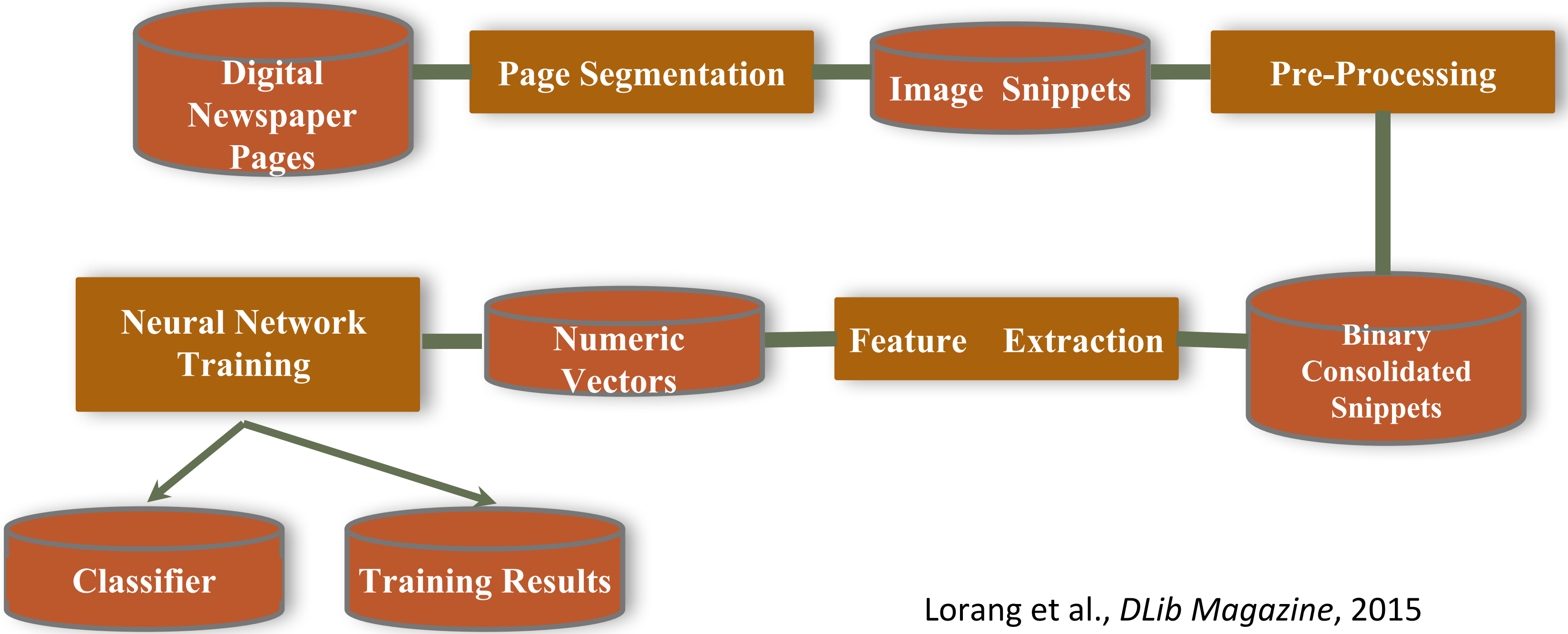
❑ **Generate data about *visual features* from the newspaper pages and then use those extracted features within a computational system, such as artificial neural network**

# Part 1: Poem Recognition

**Objectives** | Identifying existence of poem in a page

**Applications** | metadata generation, discover-/search-ability, visualization, etc.

# Poem Recognition | Workflow



Lorang et al., *DLib Magazine*, 2015

# Poem Recognition |Segmentation

## INTUITIVE STRATEGY

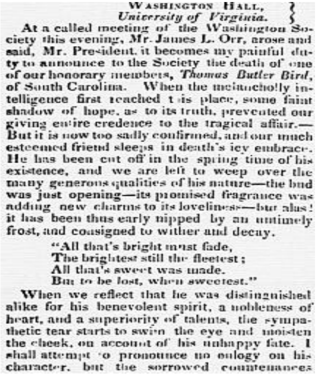
- Generate page image “snippets”
  - find the newspaper columns present on the page
  - cut each column into a series of column snippets of a fixed width:height ratio

- Take the snippet, determine whether it featured poetic content, and the determine more locally where on the page the poetic content appeared

# Poem Recognition | Segmentation

## HOWEVER …

- □ **Noticed a variety of factors influence our ability to create good image snippets**



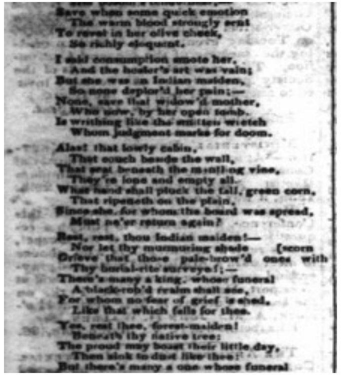
WASHINGTON HALL,
*University of Virginia.*

At a called meeting of the Washington Society this evening, Mr. James L. Orr, arose and said, Mr. President, it becomes my painful duty to announce to the Society the death of one of our honorary members, *Thomas Butler Bird*, of South Carolina. When the melancholly intelligence first reached this place, some faint shadow of hope, as to its truth, prevented our giving entire credence to the tragical affair.—But it is now too sadly confirmed, and our much esteemed friend sleeps in death's icy embrace. He has been cut off in the spring time of his existence, and we are left to weep over the many generous qualities of his nature—the bud was just opening—its promised fragrance was adding new charms to its loveliness—but alas! it has been thus early nipped by an untimely frost, and consigned to wither and decay.

"All that's bright must fade,
The brightest still the fleetest;
All that's sweet was made.
But to be lost, when sweetest."

When we reflect that he was distinguished alike for his benevolent spirit, a nobleness of heart, and a superiority of talents, the sympathetic tear starts to swim the eye and moisten the cheek, on account of his unhappy fate. I shall attempt to pronounce no eulogy on his character, but the sorrowed countenances

good quality



Save when some quick emotion
The warm blood strongly sent
To revel in her olive cheek,
So richly eloquent.

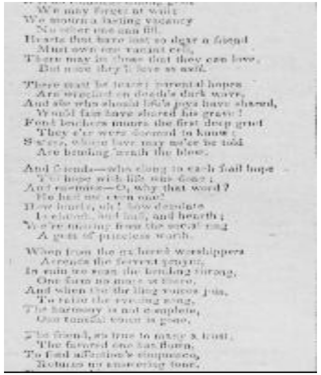
I said consumption smote her,
And the healer's art was vain;
But she was an Indian maiden,
So none deplor'd her pain;—
None, save that widow'd mother,
Who now, by her open tomb,
Is writhing like the smitten wretch
Whom judgment marks for doom.

Alas! that lowly cabin,
That couch beside the wall,
That seat beneath the mantling vine,
They're lone and empty all.
What hand shall pluck the tall, green corn,
That ripeneth on the plain,
Since she, for whom the board was spread,
Must ne'er return again?

Rest, rest, thou Indian maiden!—
Nor let thy murmuring shade (scorn
Grieve that those pale-brow'd ones with
Thy burial-rite surveyed;—
There's many a king, whose funeral
A black-rob'd realm shall see,
For whom no tear of grief is shed,
Like that which falls for thee.

Yes, rest thee, forest-maiden!
Beneath thy native tree;
The proud may boast their little day,
Then sink to dust like thee!
But there's many a one whose funeral

bleed-through



We may forget at will
We mourn a lasting vacancy
No other one can fill.
Hearts that have lost so dear a friend
Must own one vacant cell,
There may be those that they can love,
But none they'll love as well.

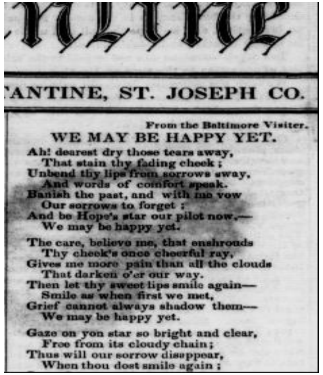
There must be tears; parental hopes
Are wrecked on death's dark wave,
And she who should life's joys have shared,
Would fain have shared his grave!
Fond brothers mourn the first deep grief
They e'er were doomed to know;
Sisters, whose love may ne'er be told
Are bending 'neath the blow.

And friends—who clung to each frail hope
Till hope with life was gone;
And enemies—O, why that word?
He had not even one!
How lonely, oh! how desolate
Is church, and hall, and hearth;
We're missing from the social ring
A gem of priceless worth.

When from the gathered worshippers
Ascends the fervent prayer,
In vain we scan the kneeling throng,
One form no more is there,
And when the thrilling voices join,
To raise the evening song,
The harmony is not complete,
One tuneful voice is gone,

The friend, so true to every trust,
The favored one has flown,
To find affection's eloquence,
Returns no answering tone.

low contrast



ntine

ANTINE, ST. JOSEPH CO.

From the Baltimore Visiter.

WE MAY BE HAPPY YET.

Ah! dearest dry those tears away,
That stain thy fading cheek;
Unbend thy lips from sorrows away,
And words of comfort speak.
Banish the past, and with me vow
Our sorrows to forget;
And be Hope's star our pilot now,—
We may be happy yet.

The care, believe me, that enshrouds
Thy cheek's once cheerful ray,
Gives me more pain than all the clouds
That darken o'er our way.
Then let thy sweet lips smile again—
Smile as when first we met,
Grief cannot always shadow them—
We may be happy yet.

Gaze on yon star so bright and clear,
Free from its cloudy chain;
Thus will our sorrow disappear,
When thou dost smile again;

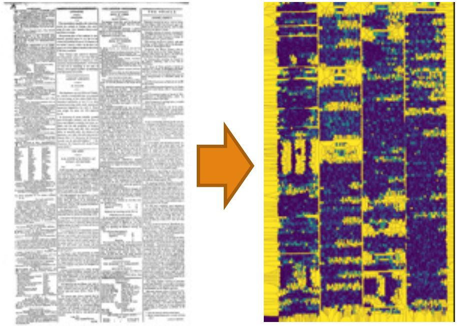
occluding "blobs"

# Poem Recognition |Segmentation

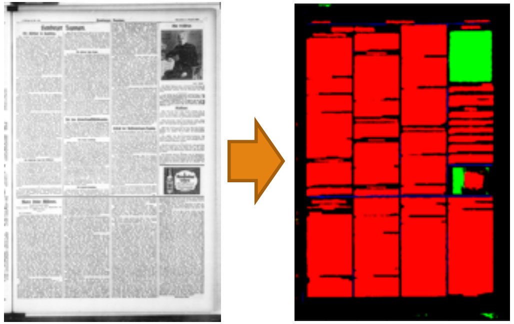
## ONGOING STRATEGIES

□ More sophisticated traditional image processing techniques; Connected component analysis (CCA), Voronoi-diagram

□ Deep-learning-based approach; dhSegment, Mask-RCNN



CCA + Voronoi-diagram

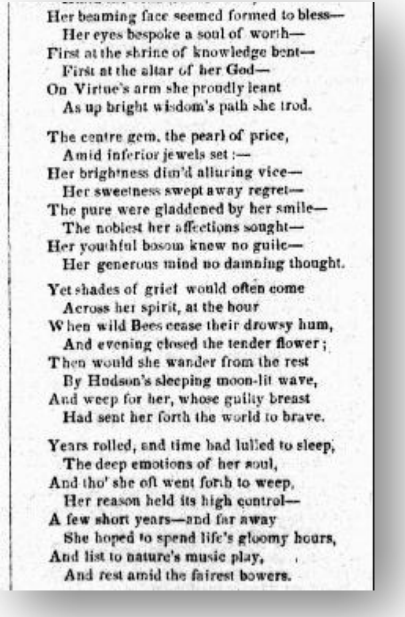


dhSegment

Mask-RCNN

# Poem Recognition | Recognition

## Which one has poem?

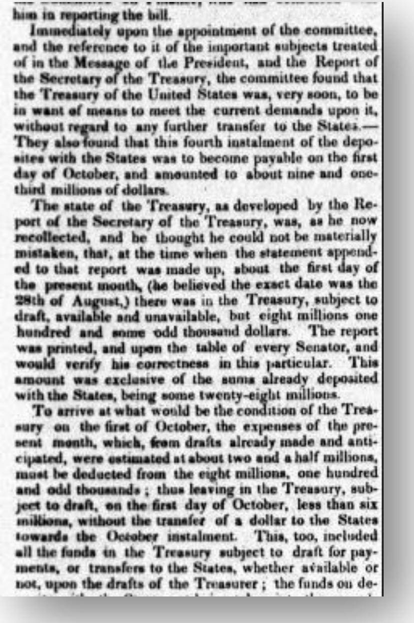


Her beaming face seemed formed to bless—
Her eyes bespoke a soul of worth—
First at the shrine of knowledge bent—
First at the altar of her God—
On Virtue's arm she proudly leant
As up bright wisdom's path she trod.

The centre gem, the pearl of price,
Amid inferior jewels set :—
Her brightness dim'd alluring vice—
Her sweetness swept away regret—
The pure were gladdened by her smile—
The noblest her affections sought—
Her youthful bosom knew no guile—
Her generous mind no damning thought.

Yet shades of grief would often come
Across her spirit, at the hour
When wild Bees cease their drowsy hum,
And evening closed the tender flower ;
Then would she wander from the rest
By Hudson's sleeping moon-lit wave,
And weep for her, whose guilty breast
Had sent her forth the world to brave.

Years rolled, and time had lulled to sleep,
The deep emotions of her soul,
And tho' she oft went forth to weep,
Her reason held its high control—
A few short years—and far away
She hoped to spend life's gloomy hours,
And list to nature's music play,
And rest amid the fairest bowers.



him in reporting the bill.

Immediately upon the appointment of the committee, and the reference to it of the important subjects treated of in the Message of the President, and the Report of the Secretary of the Treasury, the committee found that the Treasury of the United States was, very soon, to be in want of means to meet the current demands upon it, without regard to any further transfer to the States.—They also found that this fourth instalment of the deposites with the States was to become payable on the first day of October, and amounted to about nine and one-third millions of dollars.

The state of the Treasury, as developed by the Report of the Secretary of the Treasury, was, as he now recollected, and he thought he could not be materially mistaken, that, at the time when the statement appended to that report was made up, about the first day of the present month, (he believed the exact date was the 28th of August,) there was in the Treasury, subject to draft, available and unavailable, but eight millions one hundred and some odd thousand dollars. The report was printed, and upon the table of every Senator, and would verify his correctness in this particular. This amount was exclusive of the sums already deposited with the States, being some twenty-eight millions.

To arrive at what would be the condition of the Treasury on the first of October, the expenses of the present month, which, from drafts already made and anticipated, were estimated at about two and a half millions, must be deducted from the eight millions, one hundred and odd thousands ; thus leaving in the Treasury, subject to draft, on the first day of October, less than six millions, without the transfer of a dollar to the States towards the October instalment. This, too, included all the funds in the Treasury subject to draft for payments, or transfers to the States, whether available or not, upon the drafts of the Treasurer ; the funds on de-

# Poem Recognition |Recognition | Basis of Features

## Feature Extraction

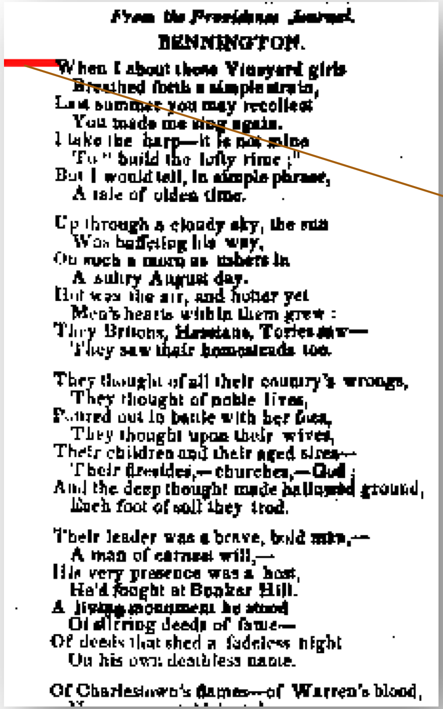
- **Left column width**
  - length of background pixels prior to the first object pixel for each row
- **Right column width**
  - length of background pixels after the final object pixel for each row
- **Row depth**
  - number of each sequence of continuous background pixels in each column
- **Margin statistics**
  - computed from the list of the Left Column Widths

# Poem Recognition |Recognition | Basis of Features

## Feature Extraction

- **Jaggedness statistic**
  - measures the number of background pixels after the final object pixel in each row
- **Stanza statistic**
  - looking for gap between stanzas using a list of Row Depths
- **Row length statistic**
  - length of continuous sequence of object pixels

# Poem Recognition |Recognition | Basis of Features



*From the Providence Journal.*

BENNINGTON.

When I about those Vineyard girls
Breathed forth a simple strain,
Last summer you may recollect
You made me sing again.
I take the harp—it is not mine
To "build the lofty rime;"
But I would tell, in simple phrase,
A tale of olden time.

Up through a cloudy sky, the sun
Was buffeting his way,
On such a morn as ushers in
A sultry August day.
Hot was the air, and hotter yet
Men's hearts within them grew:
They Britons, Hessians, Tories saw—
They saw their homesteads too.

They thought of all their country's wrongs,
They thought of noble lives,
Poured out in battle with her foes,
They thought upon their wives,
Their children and their aged sires—
Their firesides,—churches,—God;
And the deep thought made hallowed ground,
Each foot of soil they trod.

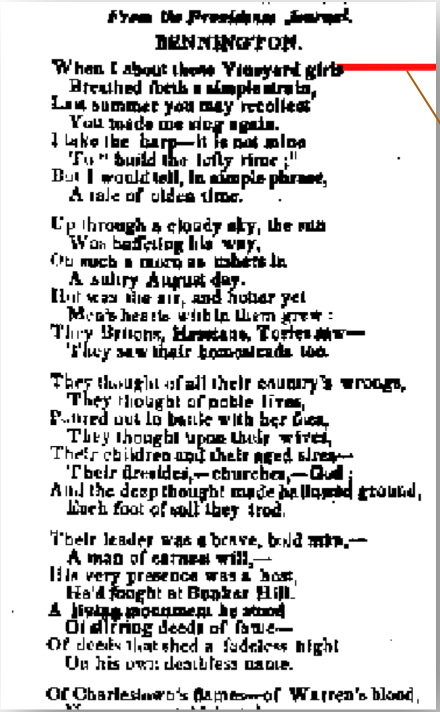
Their leader was a brave, bold man,—
A man of earnest will,—
His very presence was a host,
He'd fought at Bunker Hill.
A living monument he stood
Of stirring deeds of fame—
Of deeds that shed a fadeless light
On his own deathless name.

Of Charlestown's flames—of Warren's blood,

Left Column Widths

Length of background pixels prior to the first object pixel for each row

# Poem Recognition |Recognition | Basis of Features



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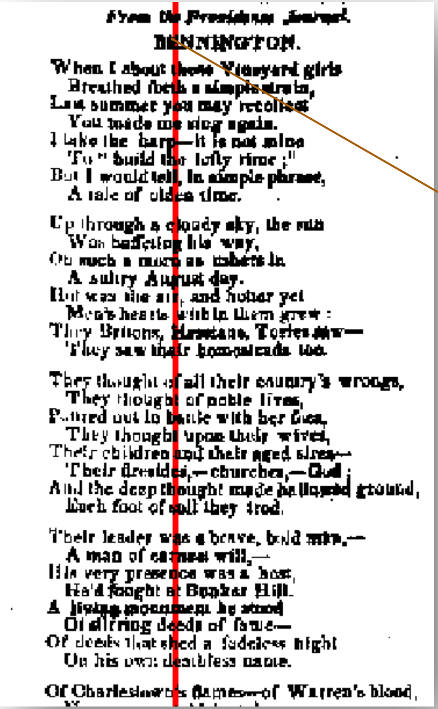

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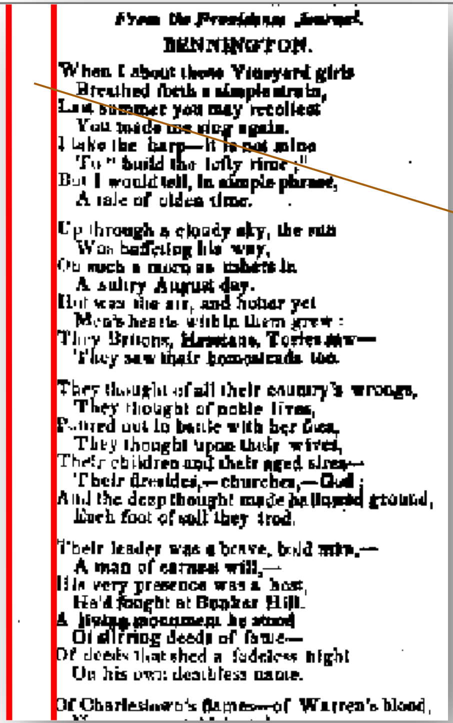
Row Depths

the number of each sequence of continuous background pixels in each column

# Poem Recognition |Recognition | Basis of Features



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Margin statistics

Computed from the list of the Left Column Widths

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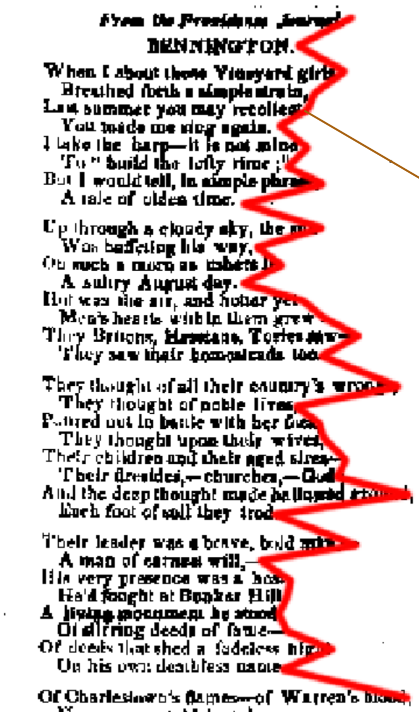

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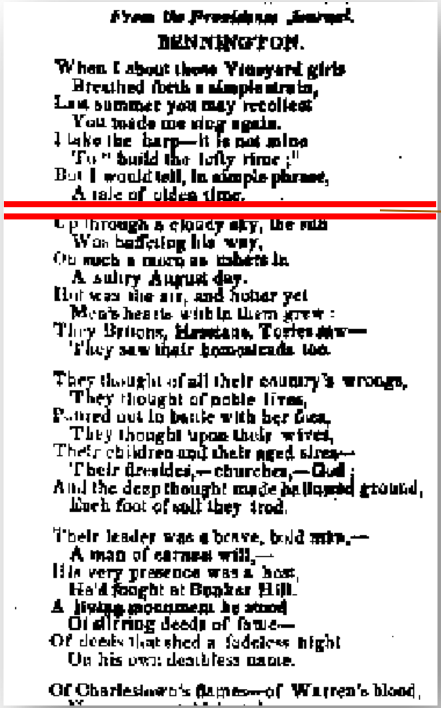

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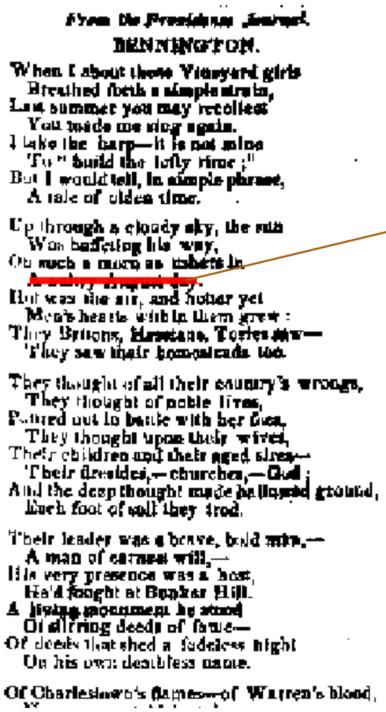
Stanza statistics

looking for gap between stanzas using a list of Row Depths

# Poem Recognition |Recognition | Basis of Features



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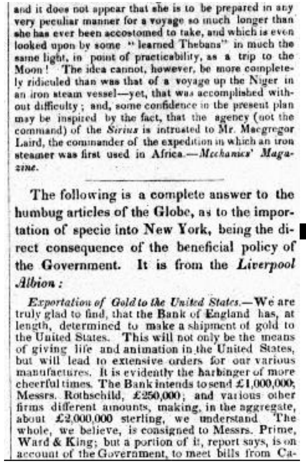
Row Length statistics

Length of continuous sequence of object pixels

# Poem Recognition |Recognition

## Snippet pre-processing

1. Otsu’s binarization [Otsu, *IEEE TSMC* 1979]
2. Consolidation [Soh, *IAAI* 2018]

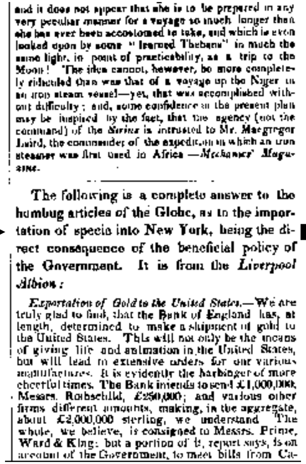


and it does not appear that she is to be prepared in any very peculiar manner for a voyage so much longer than she has ever been accostomed to take, and which is even looked upon by some "learned Thebans" in much the same light, in point of practicability, as a trip to the Moon! The idea cannot, however, be more completely ridiculed than was that of a voyage up the Niger in an iron steam vessel—yet, that was accomplished without difficulty; and, some confidence in the present plan may be inspired by the fact, that the agency (not the command) of the *Sirius* is intrusted to Mr. Macgregor Laird, the commander of the expedition in which an iron steamer was first used in Africa.—*Mechanics' Magazine.*

The following is a complete answer to the humbug articles of the Globe, as to the importation of specie into New York, being the direct consequence of the beneficial policy of the Government. It is from the *Liverpool Albion:*

*Exportation of Gold to the United States.*—We are truly glad to find, that the Bank of England has, at length, determined to make a shipment of gold to the United States. This will not only be the means of giving life and animation in the United States, but will lead to extensive orders for our various manufactures. It is evidently the harbinger of more cheerful times. The Bank intends to send £1,000,000; Messrs. Rothschild, £250,000; and various other firms different amounts, making, in the aggregate, about £2,000,000 sterling, we understand The whole, we believe, is consigned to Messrs. Prime, Ward & King; but a portion of it, report says, is on account of the Government, to meet bills from Ca-

Snippet image



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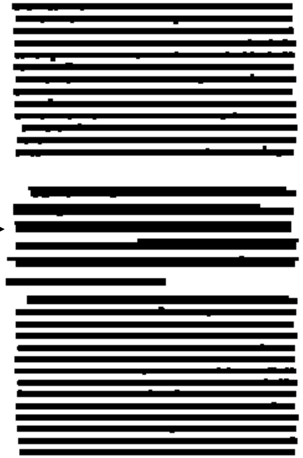
*Exportation of Gold to the United States.*—We are truly glad to find, that the Bank of England has, at length, determined to make a shipment of gold to the United States. This will not only be the means of giving life and animation in the United States, but will lead to extensive orders for our various manufactures. It is evidently the harbinger of more cheerful times. The Bank intends to send £1,000,000; Messrs. Rothschild, £250,000; and various other firms different amounts, making, in the aggregate, about £2,000,000 sterling, we understand The whole, we believe, is consigned to Messrs. Prime, Ward & King; but a portion of it, report says, is on account of the Government, to meet bills from Ca-

Binary Snippet

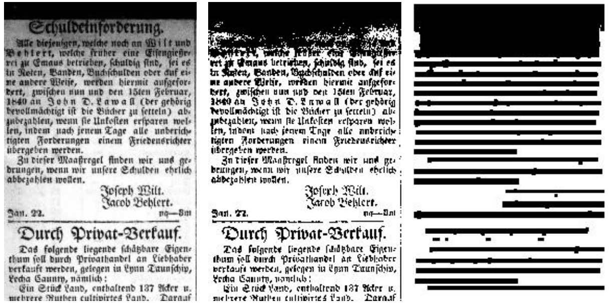


Consolidated snippet

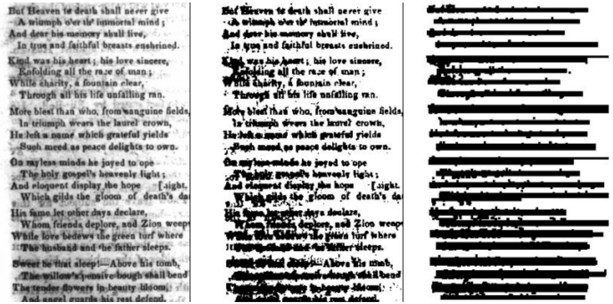
# Poem Recognition |Recognition

- Performance of feature extraction could be affected by various types of noise

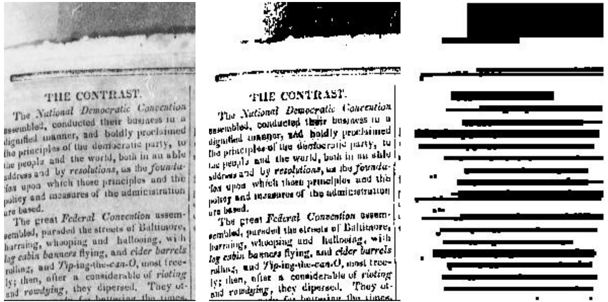
Range Effects



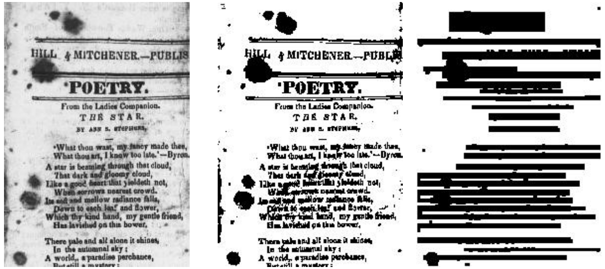
Skewed Orientation



Bleed-Through

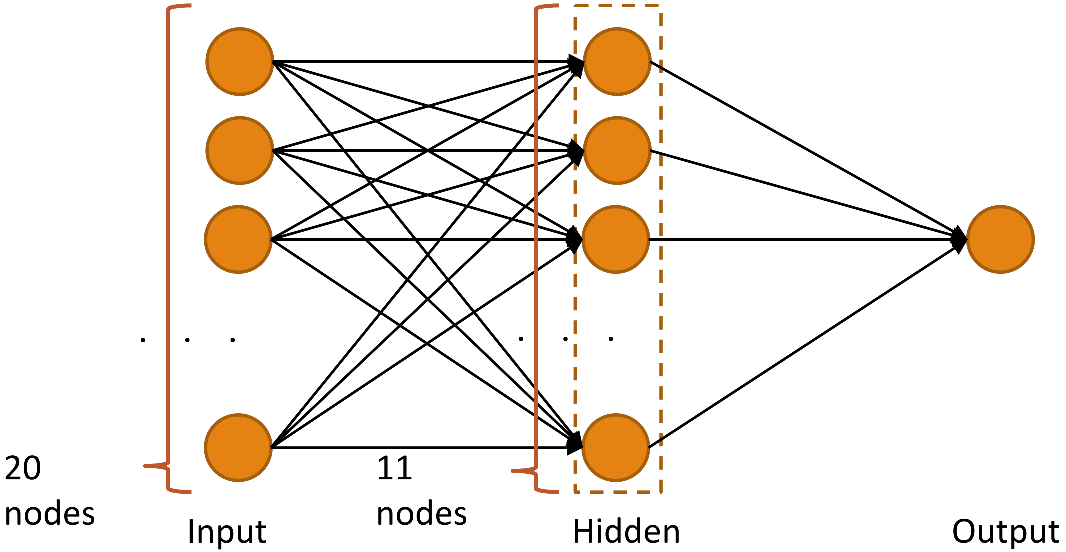


Blobs

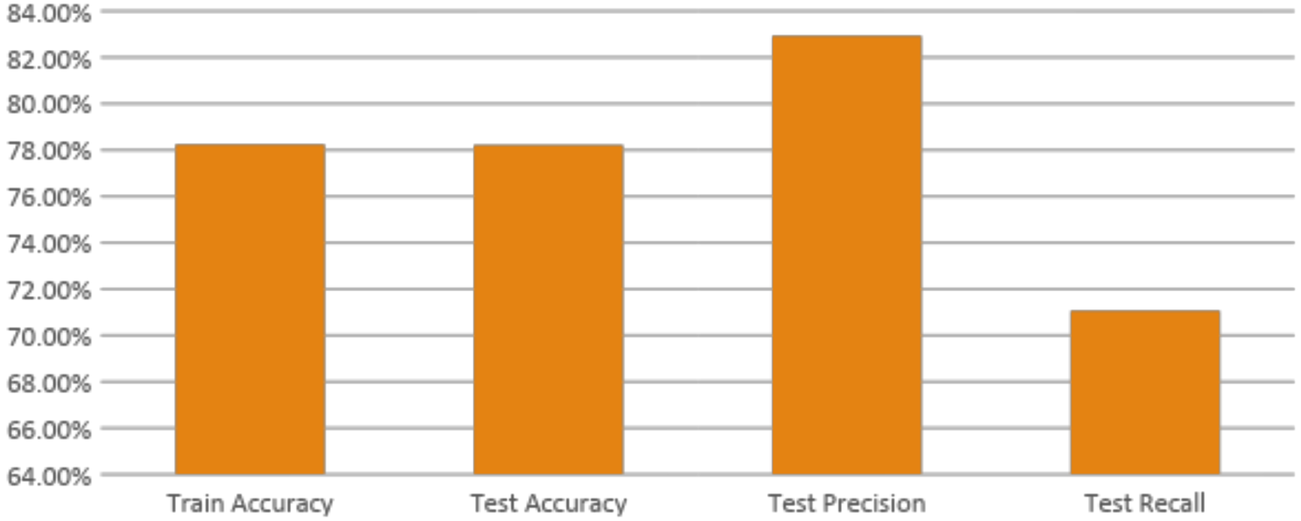


# Poem Recognition |Recognition

ANN implementation from the WEKA Workbench [Eibe et al. 2016]



# Poem Recognition |Recognition | performance



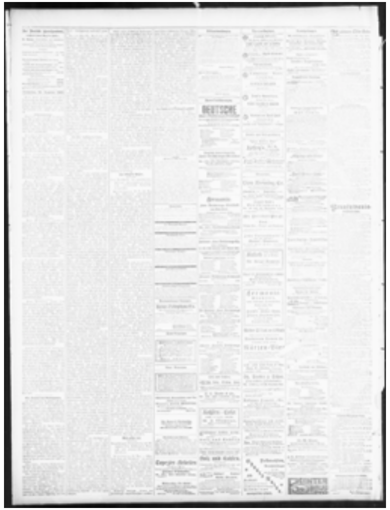
# Part 2: Document Image Quality Assessment (DIQA)

**Objectives** | Measure visual quality of document image

**Applications** | metadata generation, image quality enhancement, etc.

# DIQA |Objective

- ❑ Measure four main degradations inherent in digitized historical document images
- ❑ Analyze these measures in a large-scale dataset (i.e., Chronicling America) and interpret what they are saying



Contrast

Range-effect

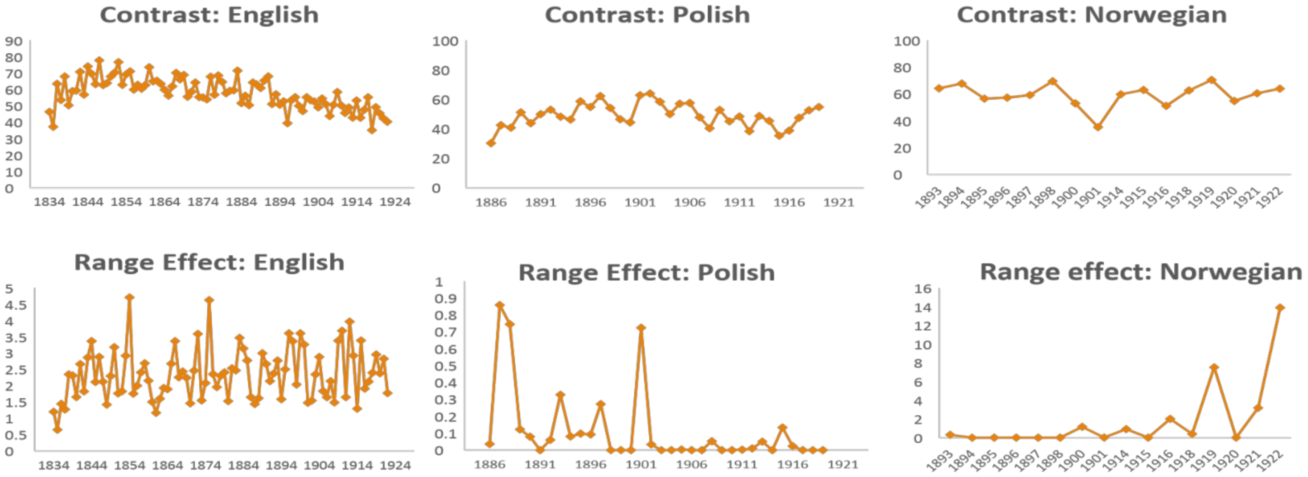
Bleed-through

Skewness

# DIQA |Contrast, Range Effect

- ❑ **Contrast** in all languages is pretty **consistent**; nor does it change drastically over time

- ❑ **Range effect**, on the other hand, not only **varies across the different languages**, it also **changes over time** for each language



Contrast: English

Contrast: Polish

Contrast: Norwegian

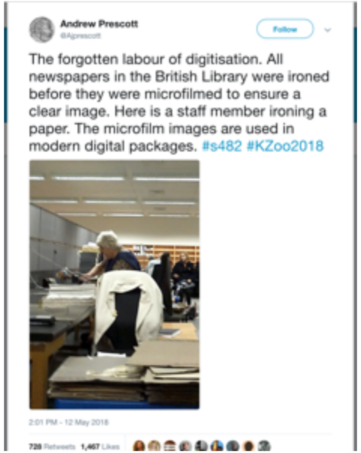
Range Effect: English

Range Effect: Polish

Range effect: Norwegian

# DIQA |Orientation Skew

- A more effective measure is likely to be local skew, relative no particular parts of the page, or other measures of warpedness or beveled nature of the page

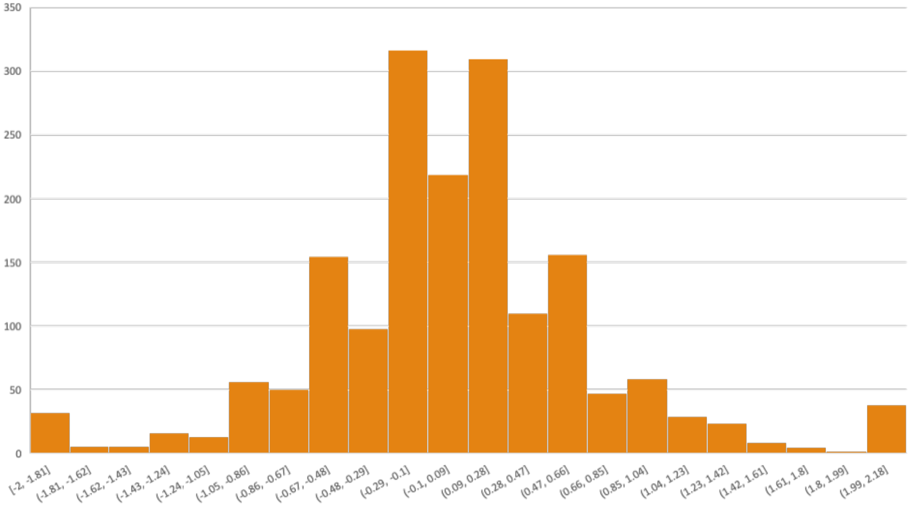


Andrew Prescott
@Ajprescott

The forgotten labour of digitisation. All newspapers in the British Library were ironed before they were microfilmed to ensure a clear image. Here is a staff member ironing a paper. The microfilm images are used in modern digital packages. #s482 #KZoo2018

2:01 PM - 12 May 2018

728 Retweets 1,467 Likes

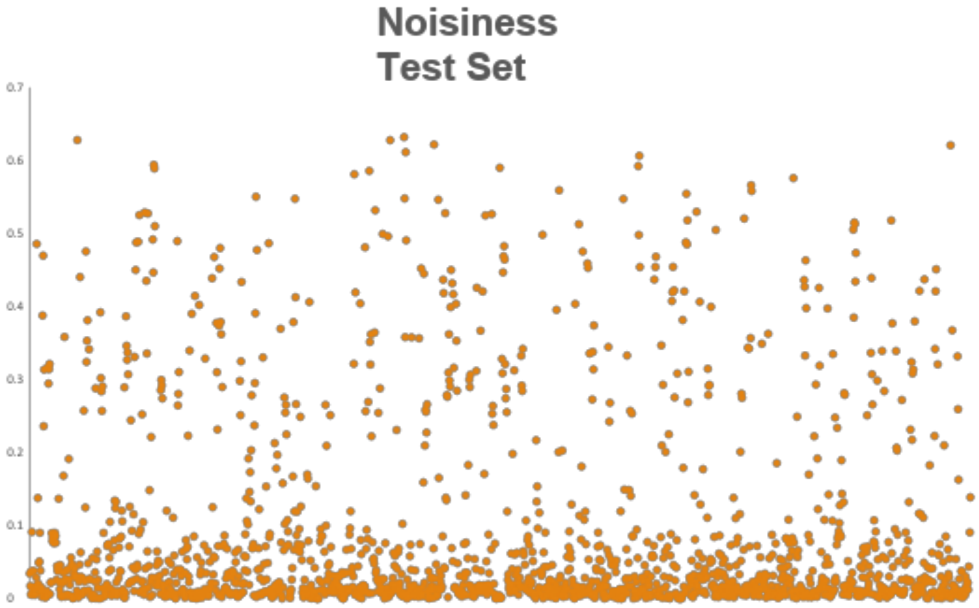


Distribution of orientation skew

# DIQA | Noisiness

❑ Assessing effects of bleed-through, blobs
(e.g., stains), and other non-textual artifacts

❑ Defects or degradations of a page, or of the digitization process based on histogram analysis—of pixels' intensity values—of each page

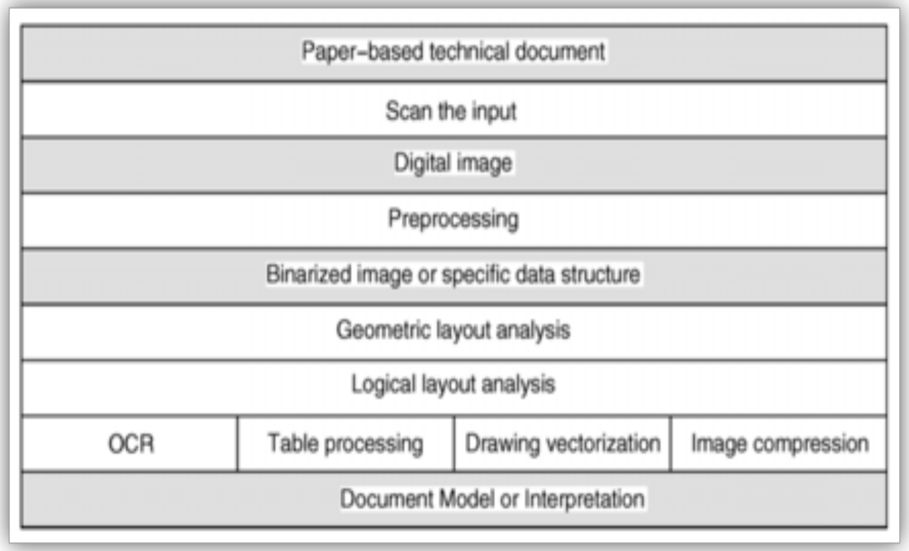


# Part 3: Zoning

**Objectives** | Segment an image into meaningful sub-regions

**Applications** | Object localization, visualization, logical layout analysis, etc.

# Zoning | Background



Paper–based technical document

Scan the input

Digital image

Preprocessing

Binarized image or specific data structure

Geometric layout analysis

Logical layout analysis

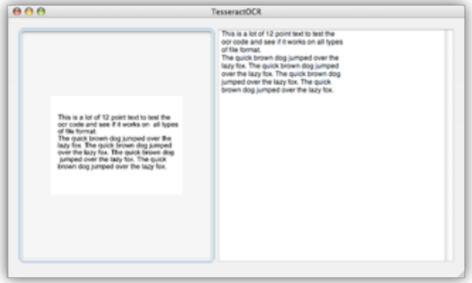
OCR

Table processing

Drawing vectorization

Image compression

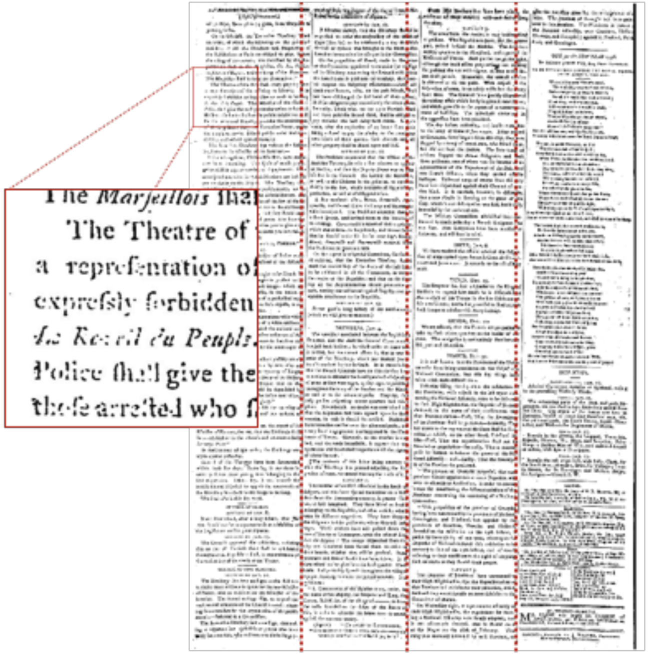
Document Model or Interpretation



This is a lot of 12 point text to test the
ocr code and see if it works on all types
of file format.
The quick brown dog jumped over the
lazy fox. The quick brown dog jumped
over the lazy fox. The quick brown dog
jumped over the lazy fox. The quick
brown dog jumped over the lazy fox.

This is a lot of 12 point text to test the
ocr code and see if it works on all types
of file format.
The quick brown dog jumped over the
lazy fox. The quick brown dog jumped
over the lazy fox. The quick brown dog
jumped over the lazy fox. The quick
brown dog jumped over the lazy fox.

# Zoning | Challenges



The Marſeillois ſhal

The Theatre of

a repreſentation of

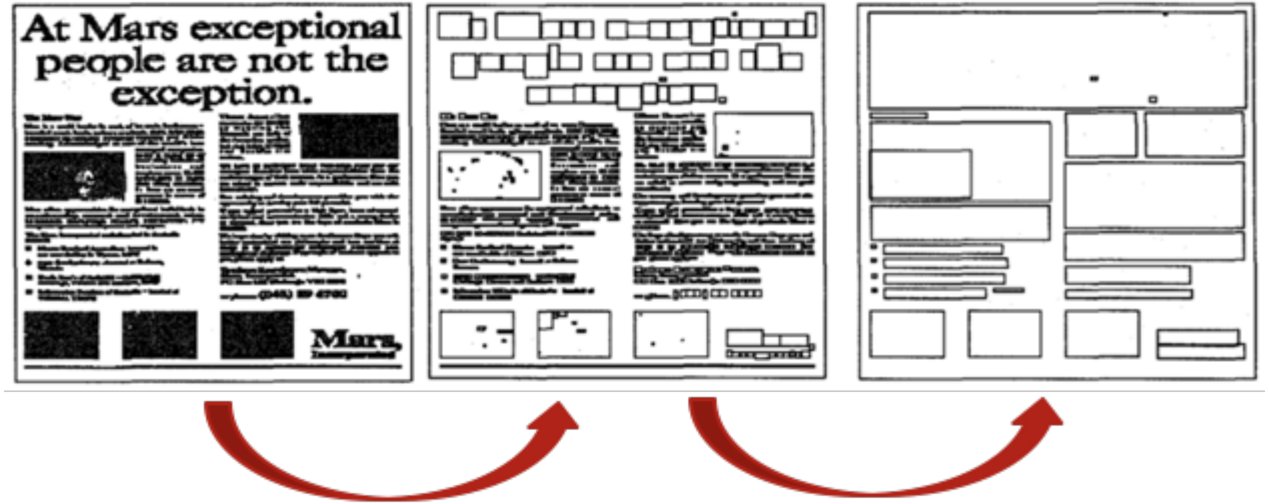
expreſsly forbidden

Le Reveil du Peuple.

Police ſhall give the

theſe arreſted who ſ

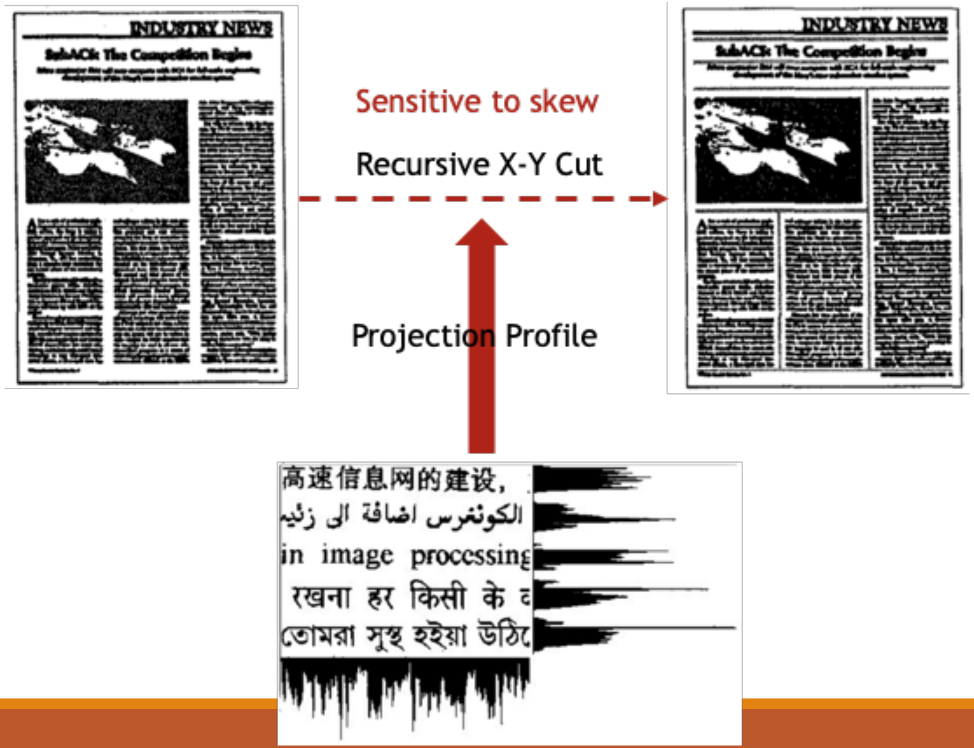
# Zoning |Traditional Approaches (Bottom-up)



Connected Component Analysis

Rule-based Merging

# Zoning |Traditional Approaches (Top-down)

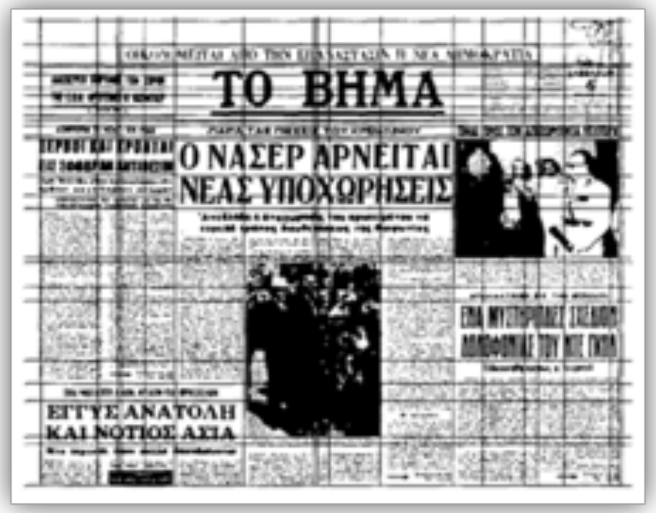


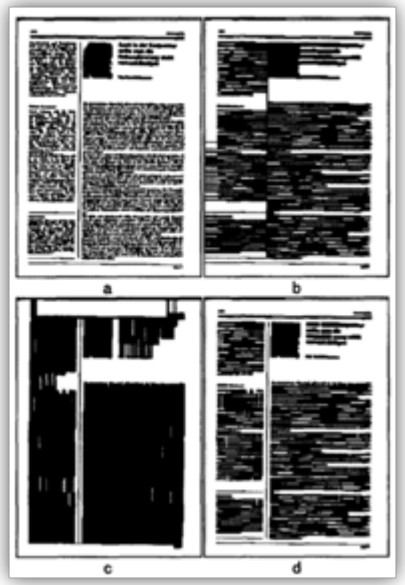
Sensitive to skew

Recursive X-Y Cut

Projection Profile

# Zoning | Traditional Approaches (Hybrid)

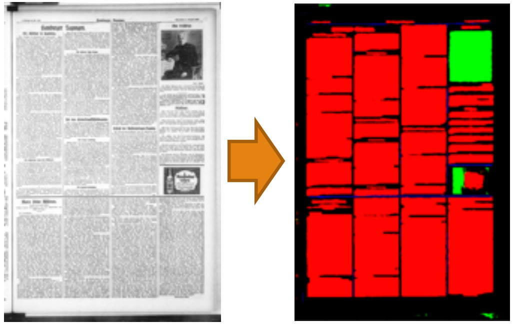




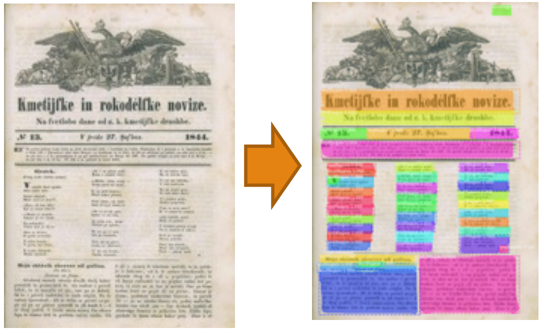
- ❑ Over-segmentation using RXYC + Merging sub-regions
- ❑ Bottom-up merging + Top-down RXYC

# Zoning | State-of-the-art Approaches (Deep Learning)

- ❑ With the advent of deep learning, it has been shown that using data-driven features, instead of hand-crafted features, is more effective
- ❑ Boundary between physical layout analysis and logical layout analysis becomes ambiguous



dhSegment


Kmetijſke in rokodelſke novize.
Kmetijſke in rokodelſke novize.

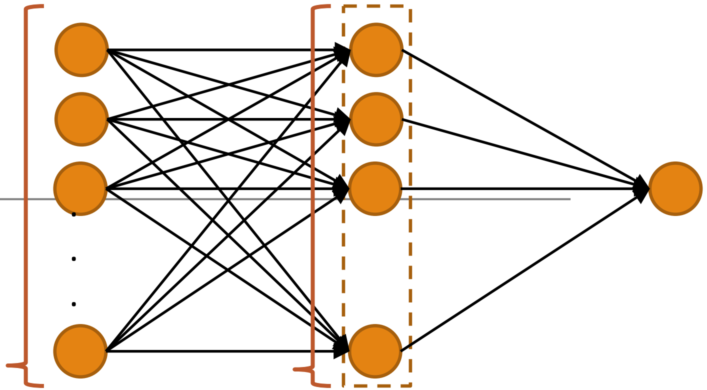
Mask-RCNN

# Part 4: Deep Learning

**Objectives** | Improve the performance of identifying existence of poem in a page

**Applications** | Automated poetic content collection, article type classification

# **Deep Learning** |Background



**Recall the ANN used in Aida project**

Generally speaking, Deep Learning is deep structured learning

Hence, *more* hidden layers

**Depending on the classification task, there are different models**

Recognizing poems in a newspaper page is an image-related classification

Hence, Convolutional Neural Network

# Deep Learning |Convolutional Neural Network

**Convolutional Neural Networks (CNN) have been shown to be effective for image-related classification**

➔ LeNet [LeCun et al.] was the start of deep CNN.

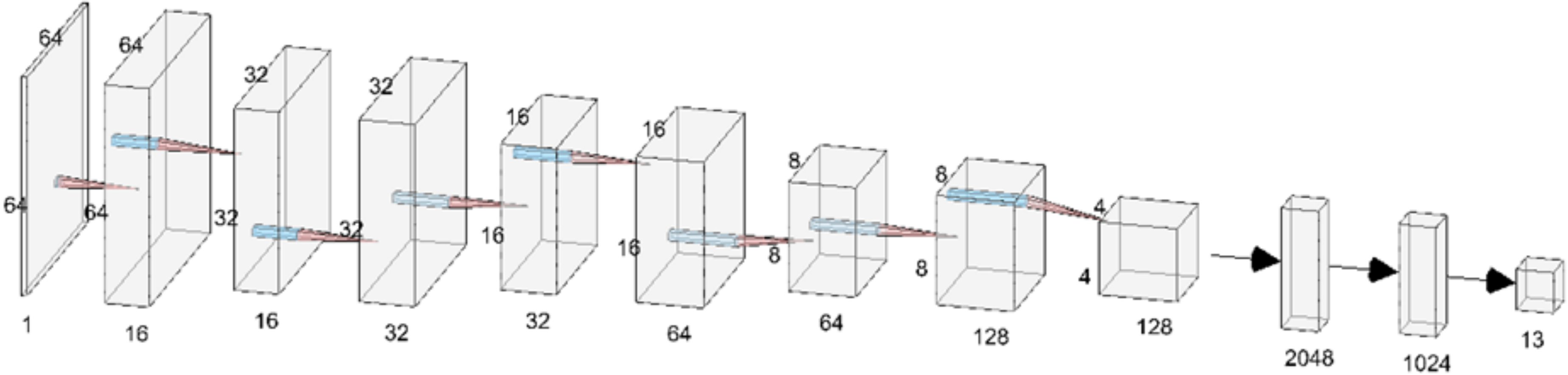
➔ AlexNet [Krizhevsky et al.] was inspired by LeNet, and outperformed state-of-art by large percentage on ImageNet.

➔ ResNet [He et al.] pushed CNN to a very deep model — 152 layer ResNet.

**More and more document image related researches were attracted**

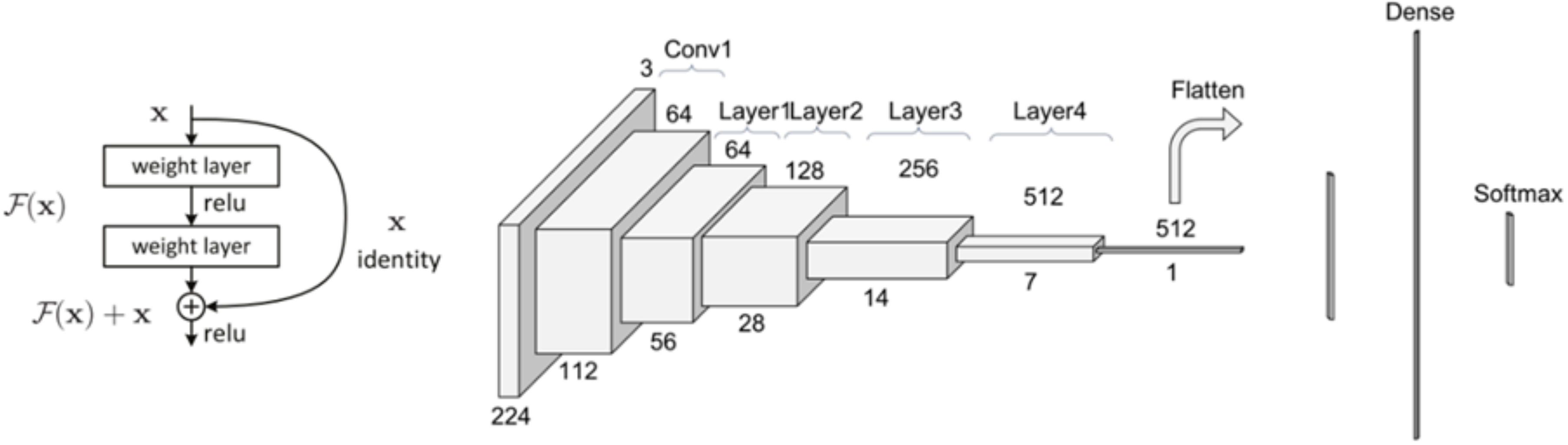
➔ Pondenkendath et al. applied ResNet to four tasks: handwritten style, document layout, authorship classification, font identification.

# Deep Learning |Convolutional Neural Network



**LeNet**

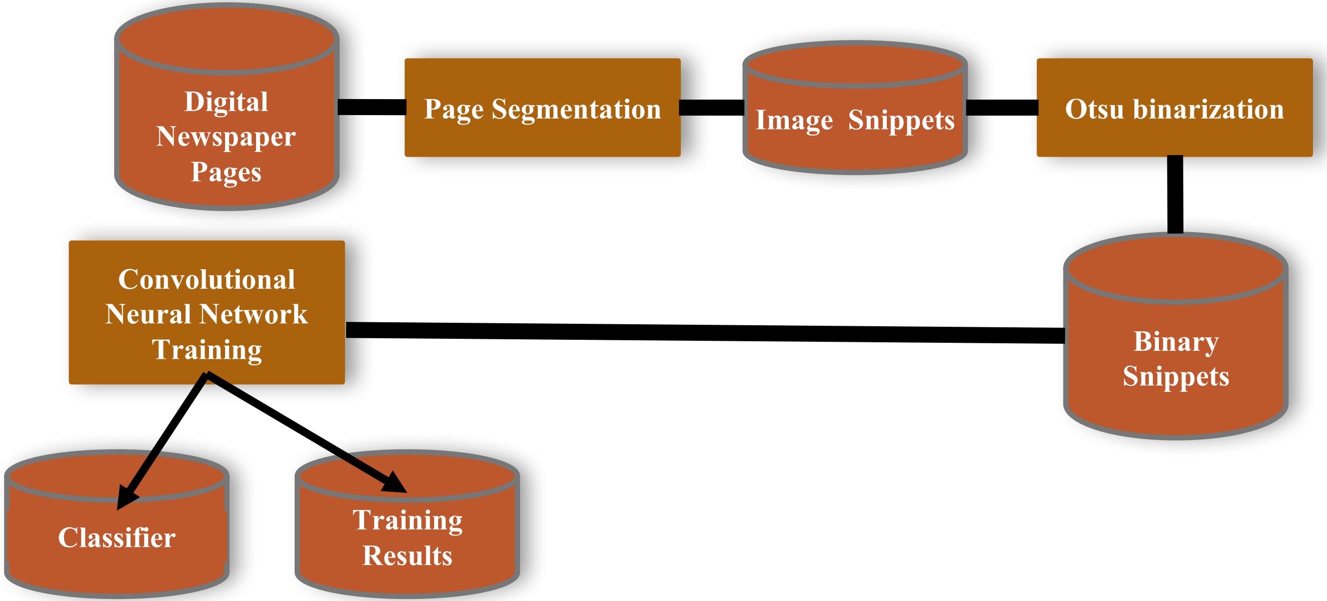
# Deep Learning |Convolutional Neural Network



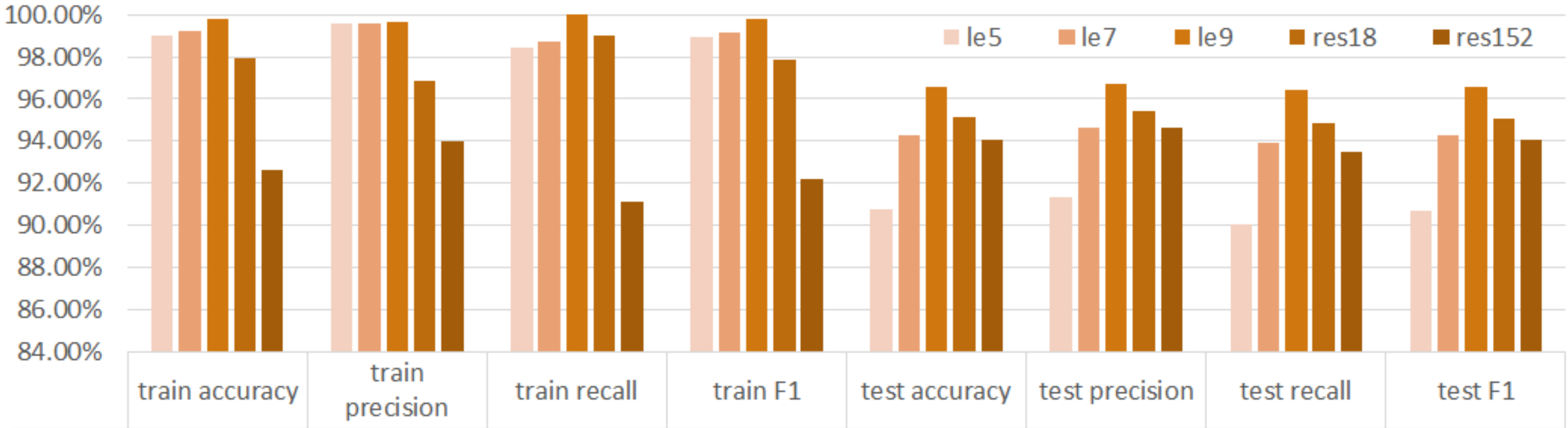
**ResNet**

# Deep Learning |2nd Gen Aida

CNN allows to learn feature from training process

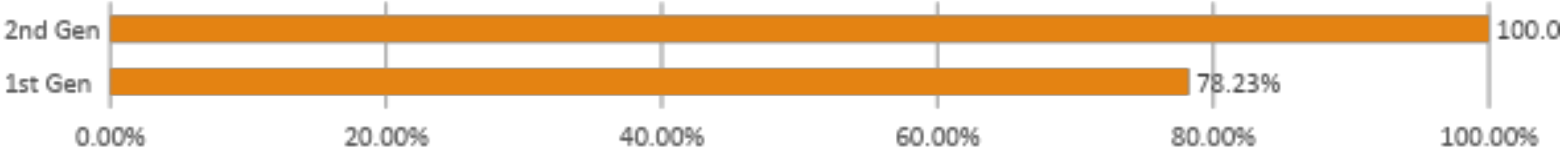


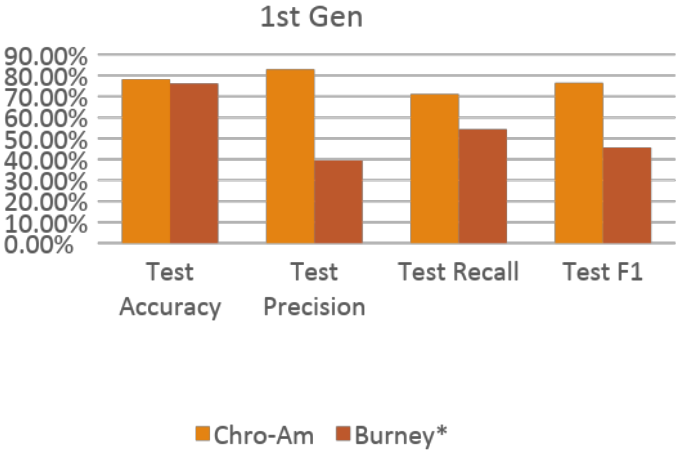
# Deep Learning |2nd Gen Aida

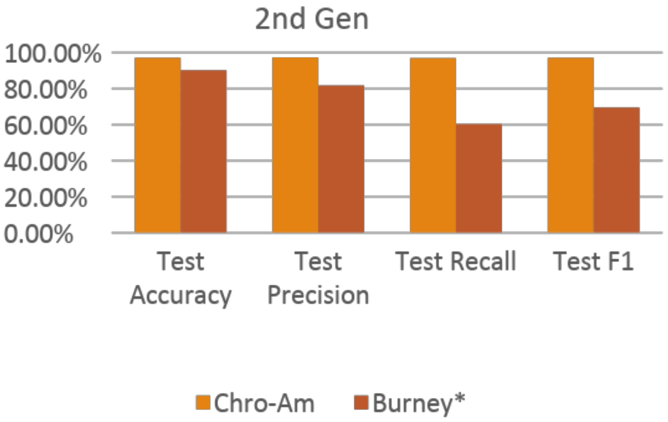


| | train accuracy | train precision | train recall | train F1 | test accuracy | test precision | test recall | test F1 |
|---|---|---|---|---|---|---|---|---|
| ■ le5 | 99.00% | 99.58% | 98.43% | 98.97% | 90.74% | 91.31% | 90.06% | 90.67% |
| ■ le7 | 99.20% | 99.58% | 98.72% | 99.12% | 94.29% | 94.61% | 93.94% | 94.27% |
| ■ le9 | **99.80%** | **99.67%** | **100.00%** | **99.83%** | **96.56%** | **96.69%** | **96.43%** | **96.56%** |
| ■ res18 | 97.91% | 96.85% | 99.05% | 97.90% | 95.11% | 95.40% | 94.83% | 95.10% |
| ■ res152 | 92.60% | 93.99% | 91.09% | 92.21% | 94.09% | 94.61% | 93.51% | 94.05% |

# **Deep Learning** | 1st vs. 2nd Gen Aida







* Burney database is not balanced, more snippets without poetic content

# **Deep Learning** | 1st vs. 2nd Gen Aida

1st Gen AIDA

Chronicling America Database

| | | **Ground-Truth** | |
|---|---|---|---|
| | | Poem | Not Poem |
| **Predicted** | Poem | 602<br>(35.54%) | 124<br>(7.32%) |
| | Not Poem | 245<br>(14.46%) | 723<br>(42.68%) |
| Correctly predicted poem snippets: 71.07%<br>and not poem snippets: 85.36% | | | |

1st Gen AIDA

Burney Collection Database

| | | **Ground-Truth** | |
|---|---|---|---|
| | | Poem | Not Poem |
| **Predicted** | Poem | 273<br>(10.02%) | 420<br>(15.41%) |
| | Not Poem | 230<br>(8.44%) | 1802<br>(66.13%) |
| Correctly predicted poem snippets: 54.27%<br>and not poem snippets: 81.10% | | | |

2nd Gen AIDA

Chronicling America Database

| | | **Ground-Truth** | |
|---|---|---|---|
| | | Poem | Not Poem |
| **Predicted** | Poem | 822<br>(48.52%) | 22<br>(1.30%) |
| | Not Poem | 25<br>(1.48%) | 825<br>(48.70%) |
| Correctly predicted poem snippets: 97.05%<br>and not poem snippets: 97.40% | | | |

2nd Gen AIDA

Burney Collection Database

| | | **Ground-Truth** | |
|---|---|---|---|
| | | Poem | Not Poem |
| **Predicted** | Poem | 304<br>(11.16%) | 68<br>(2.50%) |
| | Not Poem | 199<br>(7.30%) | 2154<br>(79.05%) |
| Correctly predicted poem snippets: 60.44%<br>and not poem snippets: 96.94% | | | |

# Deep Learning |2nd Gen Aida

**2nd Gen AIDA improved poetic content classification for historical newspaper by more than 10% comparing to 1st gen AIDA**

- 2nd Gen AIDA has over 90% test accuracies on both Chronicling America and Burney database, while 1st Gen AIDA cannot reach 80%.

**2nd Gen AIDA have potentials to generate a general classifier for other databases than the training database**

- 2nd Gen AIDA has over 90% test accuracy on Burney database.
- Precision and recall of 2nd Gen AIDA are lower than 90% but much higher than 1st Gen AIDA

# Part 5: Library of Congress
# Project 1. Document Segmentation

**Objectives** | Find and localize *Figure/Illustration/Cartoon* presented in an image

**Applications** | metadata generation, discover-/search-ability, visualization, etc.

# Background |State-of-the-Art CNN models

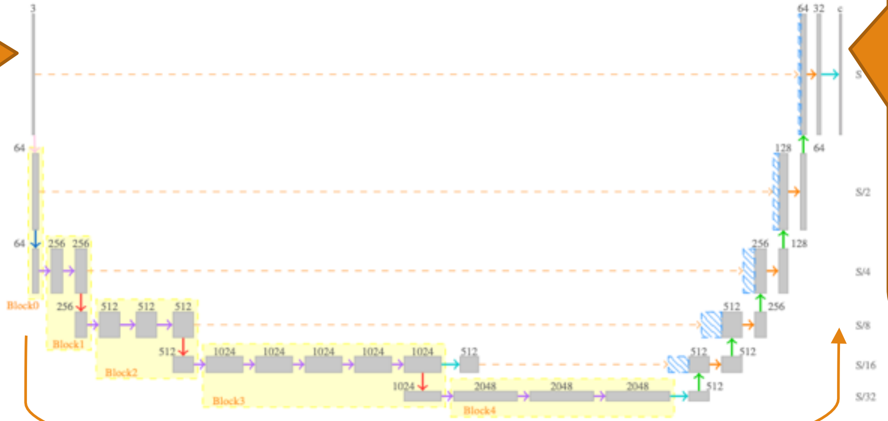
- **Convolutional Neural Network** (CNN) Models (deep learning)
  - Classification [Dataset; Top-1 / Top-5]
    - 2014, VGG-16 (Classification) [ImageNet; 74.4% / 91.9%]
    - 2015, ResNet-50 (Classification) [ImageNet; 77.2% / 93.3%]
    - 2018, ResNeXt-101 (Classification) [ImageNet; 85.1% / 97.5%]
  - Segmentation [Dataset; Intersection-over-Union (IoU)]
    - 2015, U-net (Segmentation/Pixel-wise classification) [ISBI; 92.0%]

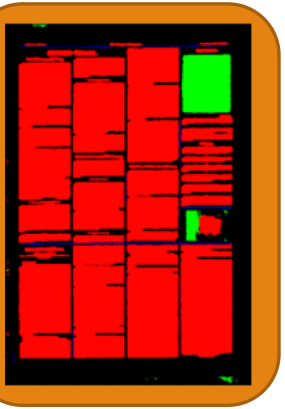
- So, we now know that CNNs achieve *remarkable* performances in both classification and segmentation tasks.
- ***What about document images then?***

# Document Segmentation | Technical Details

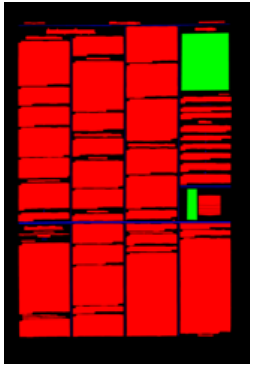
- ***Training*** is a process of finding the optimal value weights between artificial neurons that minimizes a pre-defined ***loss*** function

Input





Prediction



Ground-truth

1. Convolution & Down-sampling:
understand "***WHAT***" is present in the image (i.e., feature extraction)

2. Up-sampling:
understand "***WHERE***" it is present in the image

3. Calculate per-pixel loss
4. Update weights between neurons
5. Repeat the process

# Document Segmentation | Dataset

## Beyond Words

- Total of 2,635 image snippets from 1,562 pages (as of 7/24/2019)
  - 1,027 pages with single snippet
  - 512 pages with multiple snippets
- Issues
  - Inconsistency (Figure 1)
  - Imprecision (Figure 2)
  - Data imbalance (Figure 3)

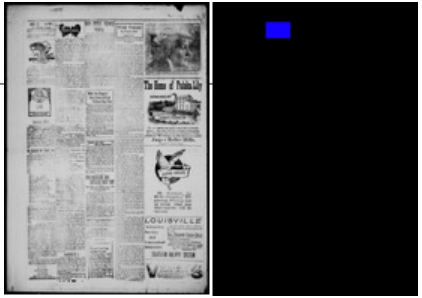
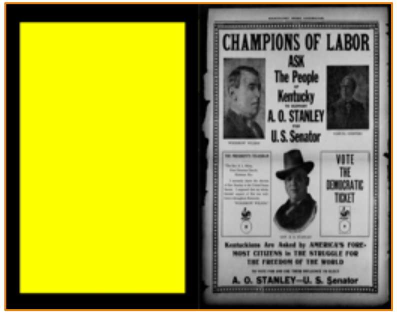


Figure 1. Example of inconsistency. Note that there are more than one image snippets in the left image (i.e. input) while there is only a single annotation in the right ground-truth.



CHAMPIONS OF LABOR
ASK
The People
Kentucky
A. O. STANLEY
U. S. Senator
VOTE
THE
DEMOCRATIC
TICKET
Kentuckians Are Asked by AMERICA'S FORE-MOST CITIZENS in THE STRUGGLE FOR THE FREEDOM OF THE WORLD
A. O. STANLEY—U. S. Senator

Figure 2. Example of imprecision. From left to right: (1) ground-truth (yellow: Photograph and black: background) and (2) original image. Note here that in the ground-truth, non-photograph-like (e.g., texts) components are included within the yellow rectangle region.

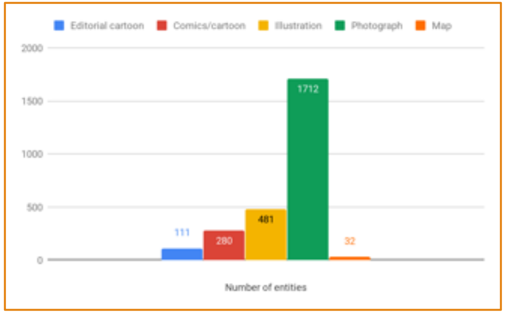


Figure 3. Number of snippets in Beyond Words. Note here the data imbalance

# Document Segmentation | Dataset

## European Historical Newspapers (ENP)

- Total of 57,339 image snippets in 500 pages
  - All pages have multiple snippets
- Issues
  - Data imbalance
    - Text: 43,780
    - Figure: 1,452
    - Line-separator: 11,896
    - Table: 221

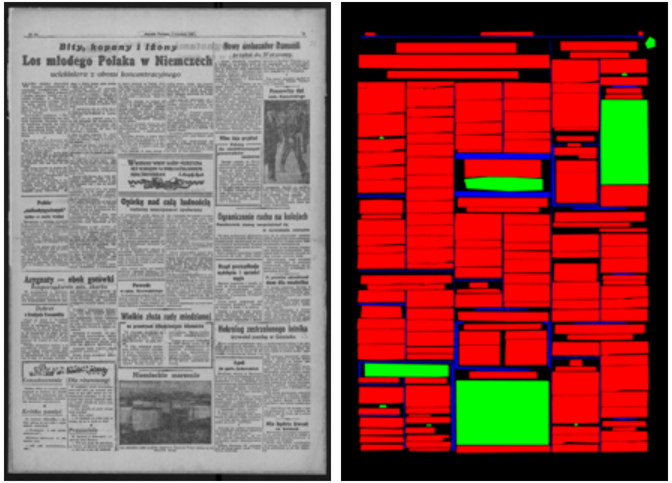
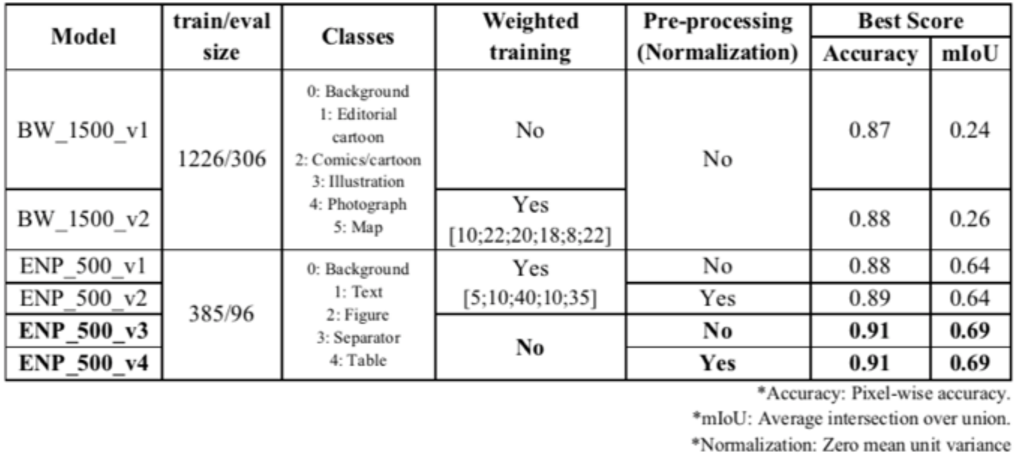


Figure 4. Example of image (left) and ground-truth (right) from ENP dataset. In the ground-truth, each color represents the following components: (1) black: background, (2) red: text, (3) green: figure, (4) blue: line-separator, and (5) yellow: table.

# Document Segmentation | Experimental Results

- ❑ A U-net model trained with ENP dataset shows better segmentation performance than that with Beyond Words in terms of pixelwise-accuracy and IoU score
  - ❑ IoU score is a commonly used metric to evaluate segmentation performance
  - ❑ The three issues—inconsistency, imprecision, and data imbalance—of Beyond Words dataset need to be improved for better use in training



| Model | train/eval size | Classes | Weighted training | Pre-processing (Normalization) | Best Score | |
|---|---|---|---|---|---|---|
| | | | | | Accuracy | mIoU |
| BW_1500_v1 | 1226/306 | 0: Background<br>1: Editorial cartoon<br>2: Comics/cartoon<br>3: Illustration<br>4: Photograph<br>5: Map | No | No | 0.87 | 0.24 |
| BW_1500_v2 | | | Yes [10;22;20;18;8;22] | | 0.88 | 0.26 |
| ENP_500_v1 | 385/96 | 0: Background<br>1: Text<br>2: Figure<br>3: Separator<br>4: Table | Yes [5;10;40;10;35] | No | 0.88 | 0.64 |
| ENP_500_v2 | | | | Yes | 0.89 | 0.64 |
| **ENP_500_v3** | | | **No** | **No** | **0.91** | **0.69** |
| **ENP_500_v4** | | | | **Yes** | **0.91** | **0.69** |

*Accuracy: Pixel-wise accuracy.
*mIoU: Average intersection over union.
*Normalization: Zero mean unit variance

- ❑ Assigning different weights per class to mitigate data imbalance did *not* show performance improvement
  - ❑ ***Future Work:*** Explore a different way of weighting strategy to mitigate a data imbalance problem

# Document Segmentation | Potential Applications 1

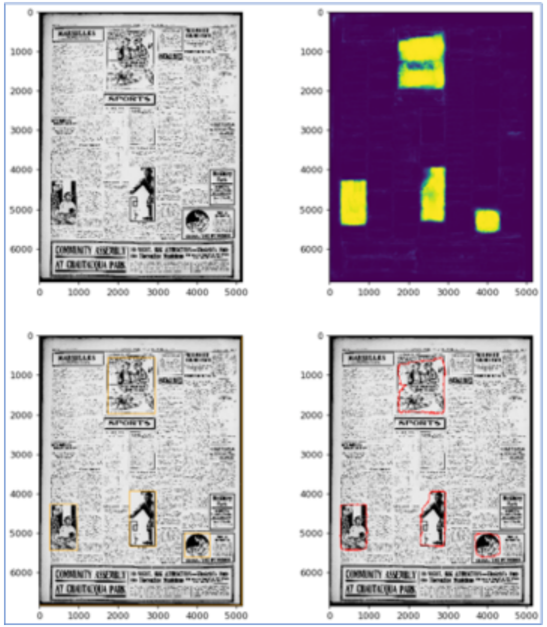


Figure 5. Segmentation result of ENP_500_v4 on Chronicling America image (sn92053240-19190805.jpg). Clockwise from top- left: (1) Input, (2) probability map for figure class, (3) detected figures in polygon, and (4) detected figures in bounding-box. In the probability map, pixels with higher probability to belong to figure class are shown with brighter color.

- Enrich page-level metadata by cataloging the types of visual components presented on a page
- Enrich collection-level metadata as well
- Visualize figures’ locations on a page

# Document Segmentation | Potential Applications 2

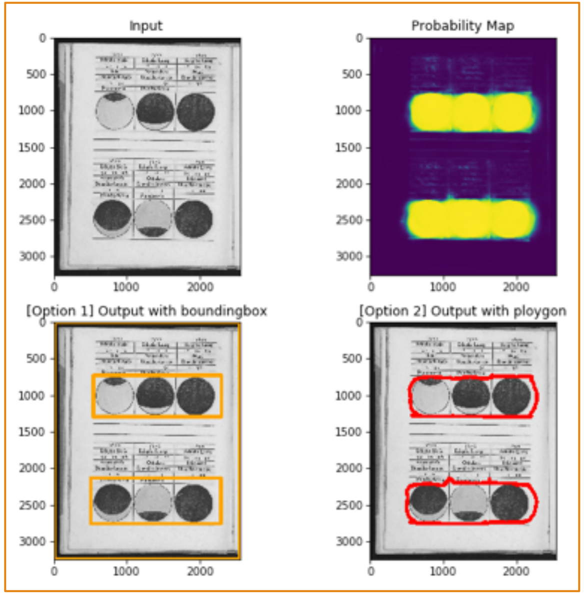
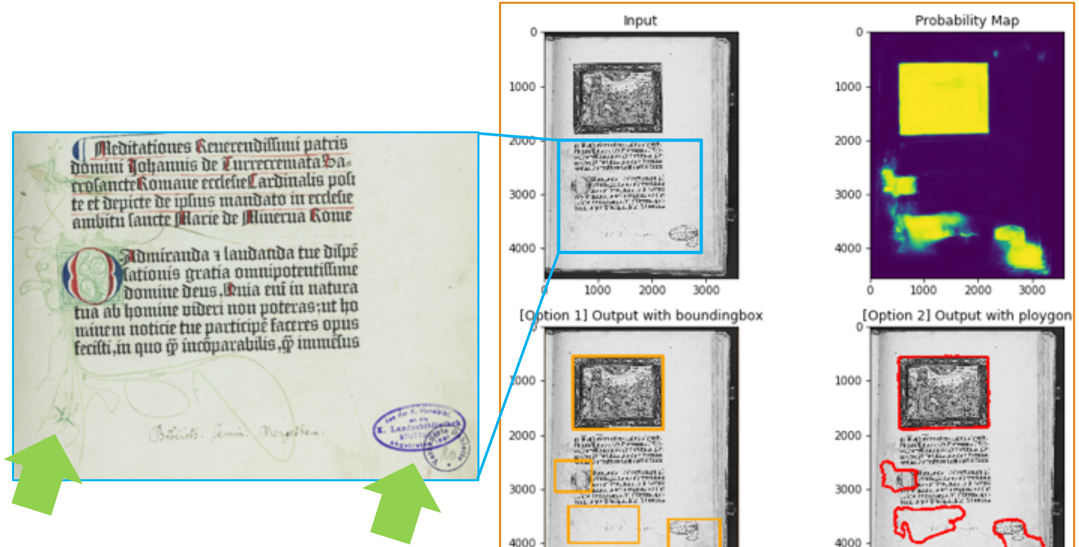


Figure 6. Successful segmentation result of ENP_500_v4 on book/printed material (https://www.loc.gov/resource/rbc0001.2013rosen0051/?sp=37).



Meditationes Reuerendiſſimi patris domini Johannis de Turrecremata Sacroſancte Romane eccleſie Cardinalis poſite et depicte de ipſius mandato in eccleſie ambitu ſancte Marie de Minerua Rome

O Admiranda ⁊ laudanda tue diſpēſationis gratia omnipotentiſſime domine deus. Quia cū in natura tua ab homine uideri non poteras; ut humanem noticie tue participē faceres opus feciſti, in quo ꝙ icōparabilis, ꝙ immēſus

Biblioth. Semin. Norgelten.

Figure 7. Failure segmentation result of ENP_500_v4 on book/printed material (https://cdn.loc.gov/service/rbc/rbc0001/2010/2010rosen0073/0005v.jpg). Note that there is light drawing or stamps (marked in green arrows) on the false positive regions.

# Document Segmentation | Conclusions

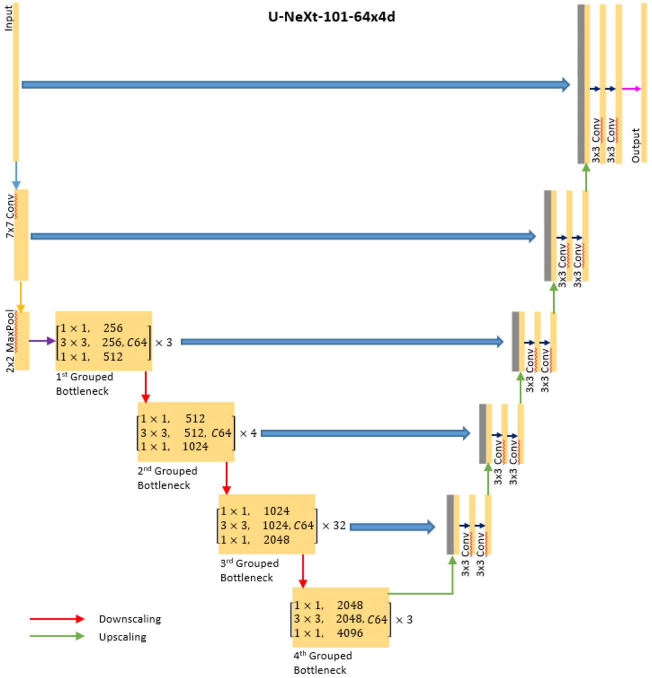
- As a preliminary experiment, a state-of-the-art CNN model (i.e., U-net) shows promising segmentation performance on ENP document image dataset,
  - There is still room for improvement with more sophisticated training strategies (e.g., weighted training, augmentation, etc.)
- To make Beyond Words dataset more as a valuable training resource for machine learning researchers, we need to address the following issues:
  - Consistency
  - Precision of the coordinates of regions

# Part 5: Library of Congress
# Project 2.1. Figure/Graph Extraction

**Objectives** | Find and localize *Figure*/Graph in a document image

**Applications** | Graph retrieval, document segmentation based on content type

# Figure/Graph Extraction | Technical Details


U-NeXt-101-64x4d
Input
7x7 Conv
2x2 MaxPool
$\begin{bmatrix}1\times1, & 256\\3\times3, & 256, C64\\1\times1, & 512\end{bmatrix}\times 3$
1st Grouped Bottleneck
$\begin{bmatrix}1\times1, & 512\\3\times3, & 512, C64\\1\times1, & 1024\end{bmatrix}\times 4$
2nd Grouped Bottleneck
$\begin{bmatrix}1\times1, & 1024\\3\times3, & 1024, C64\\1\times1, & 2048\end{bmatrix}\times 32$
3rd Grouped Bottleneck
$\begin{bmatrix}1\times1, & 2048\\3\times3, & 2048, C64\\1\times1, & 4096\end{bmatrix}\times 3$
4th Grouped Bottleneck
3x3 Conv
3x3 Conv
Output
Downscaling
Upscaling

An FCN (U-NeXt) is used

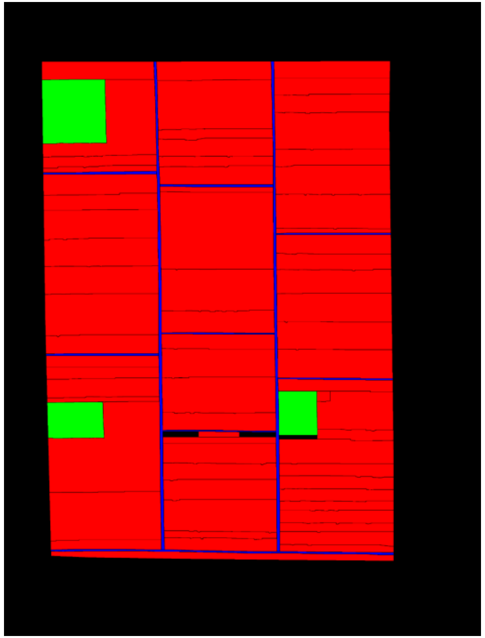
- U-NeXt combines ResNeXt and U-Net
  - ResNeXt101_64x4d
- Why ResNeXt101_64x4d?
  - Current state-of-art
  - Accessible pre-trained model
- **Transfer learning**
  - ResNeXt101_64x4d
  - Number of parameters:
    - 114.4 million ⍰ 32.8 million

# Figure/Graph Extraction | Datasets

- ❑ **ENP collection**: European newspaper collection
  - ❑ A subset used for the International Conference on Document Analysis and Recognition competition
- ❑ **Beyond Word collection**: Transcribed collection
  - ❑ But cannot be used for training directly …
    - ❑ Problem 1: missing figures in ground-truth
    - ❑ Problem 2: inaccurate ground-truth

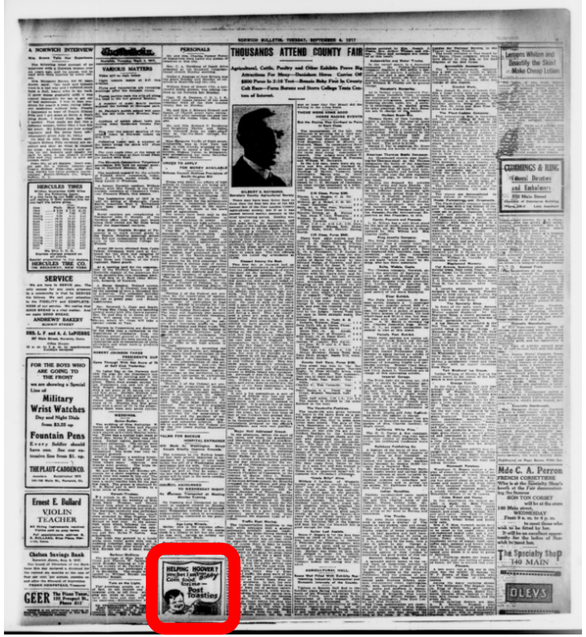
# Figure/Graph Extraction | Datasets: ENP

Document Image

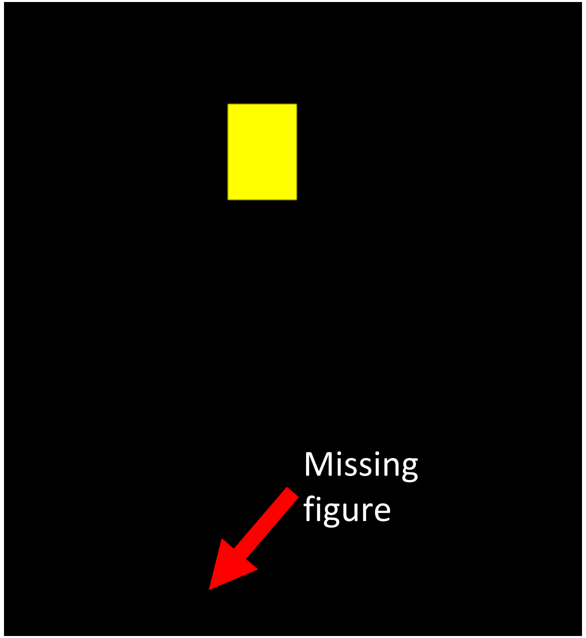


Ground-truth

# Figure/Graph Extraction | Datasets: Beyond Words



Document Image



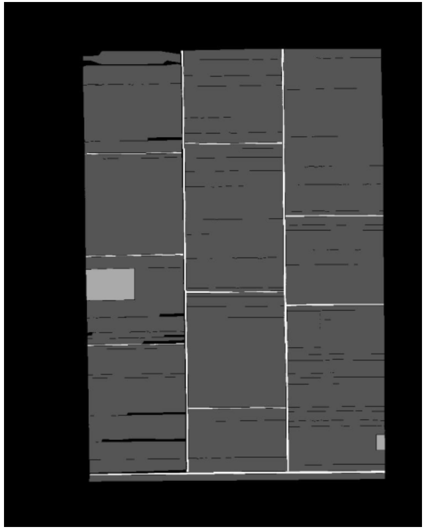
Missing figure

Ground-truth

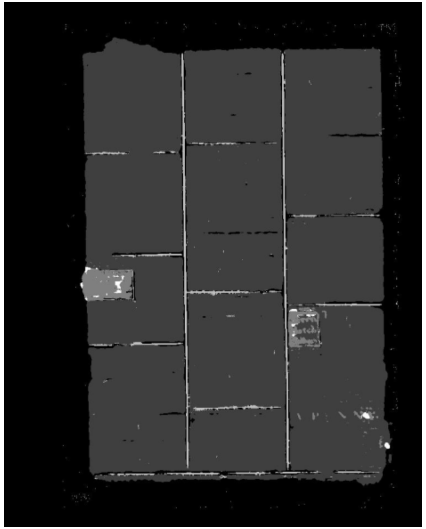
# Figure/Graph Extraction | Preliminary Results

- ❑ Transfer parameters from pre-trained ResNeXt101 64x4d
- ❑ Trained on ENP dataset

Document
Image



Ground
truth

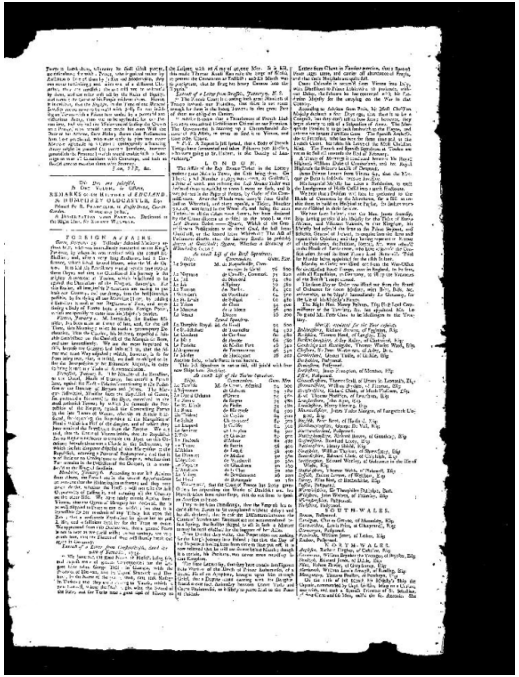


Predictio
n

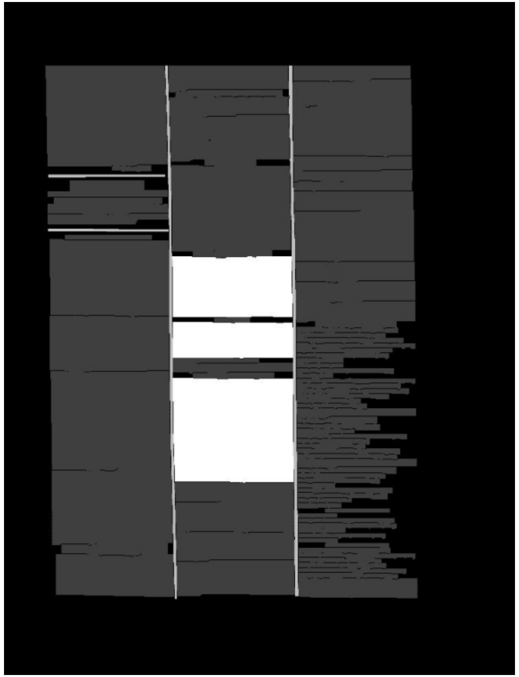
# Figure/Graph Extraction | Conclusions

- Promising preliminary results
- Potential applications
  - Segmentation based on content type to increase item-level accessibility
  - Retrieval of figures/graphs for further study
- Challenges
  - U-NeXt still needs more iterations of training
  - Preliminary training indicates that tables may be the hardest type to extract

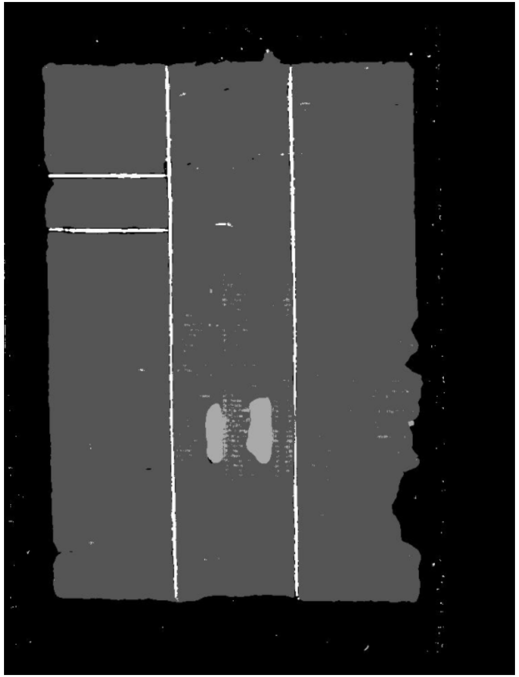
# Figure/Graph Extraction | Challenge



Document Image



Ground truth



Predictio n

# Part 5: Library of Congress
# Project 2.1. Text Extraction from Figure/Graph

**Objectives** | Extract texts from figure/graph

**Applications** | Metadata generation, OCR for figure/graph caption

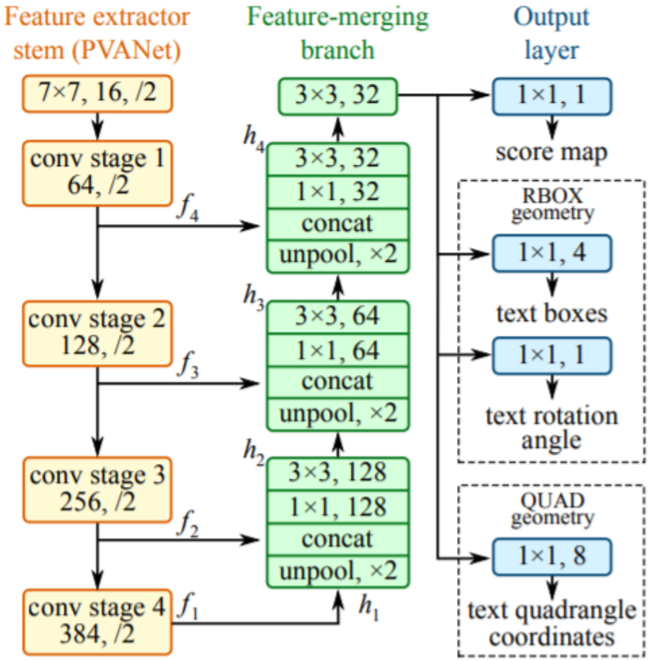
# Text Extraction from Figure/Graph | Technical Details

## EAST text detector

- ❑ EAST: Efficient and Accurate Scene Text detector
- ❑ HyperNet + U-Net
- ❑ Detect texts in graphic images in any direction

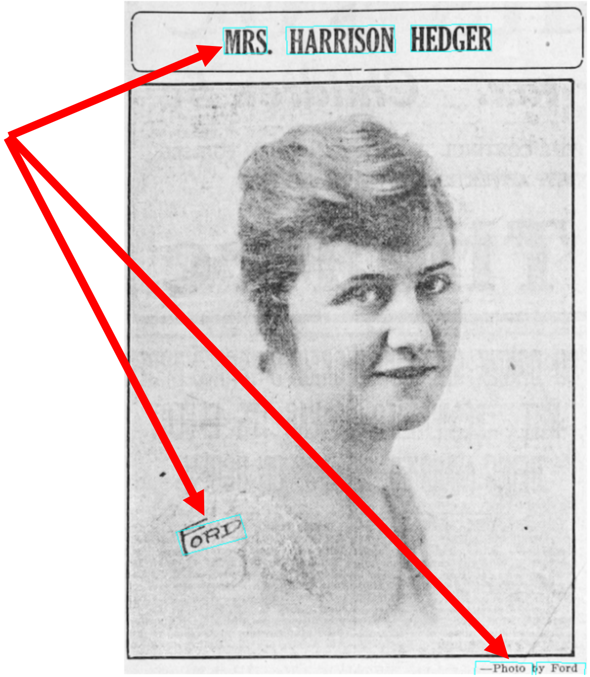
Why applicable?

- ❑ figures/illustrations are snippets of a graphic region

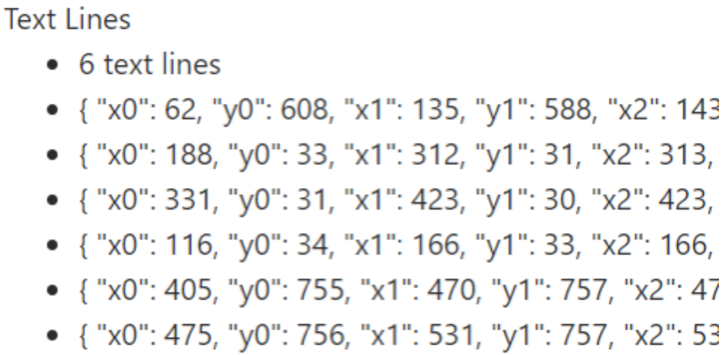


# Text Extraction from Figure/Graph | Preliminary Results

Detected Texts



- ❑ Performance on detecting texts in newspaper figure/graph is good
- ❑ Texts location is recorded



Text Lines

- 6 text lines
- { "x0": 62, "y0": 608, "x1": 135, "y1": 588, "x2": 143
- { "x0": 188, "y0": 33, "x1": 312, "y1": 31, "x2": 313,
- { "x0": 331, "y0": 31, "x1": 423, "y1": 30, "x2": 423,
- { "x0": 116, "y0": 34, "x1": 166, "y1": 33, "x2": 166,
- { "x0": 405, "y0": 755, "x1": 470, "y1": 757, "x2": 47
- { "x0": 475, "y0": 756, "x1": 531, "y1": 757, "x2": 53

# Text Extraction from Figure/Graph | Conclusions

- ❑ Promising preliminary results
- ❑ Potential application
  - ❑ Perform OCR on detected text regions for higher accuracy
  - ❑ Extract OCR-ed words in detected text regions as metadata

# Part 5: Library of Congress
# Project 3. Document Type Classification

**Objectives** | (1) Classify a given image into one of *Handwritten/Typed/Mixed* type; (2) Classify a given image into one of *Scanned/Microfilmed*

**Applications** | metadata generation, discover-/search-ability, cataloging, etc.

# Document Type Classification | Technical Details

*Note that we do not need up-sampling in this task, since **WHERE** is not our concern*

- ❑ A simple VGG-16 is used (Figure 8)
  - ❑ Afzal et al. reported that most of state-of-the-art CNN models yielded around 89% of accuracy on document image classification task
- ❑ **Transfer learning?**
  - ❑ Why don’t we initialize our model’s weights from a model that has been already trained on a large-scale data, such as *ImageNet* (about 14M images)?
  - ❑ ***Why?*** (1) training a model from the scratch (i.e., the value of weights between neurons are initialized to random number) takes too much time; (2) we have too small a dataset to train a model

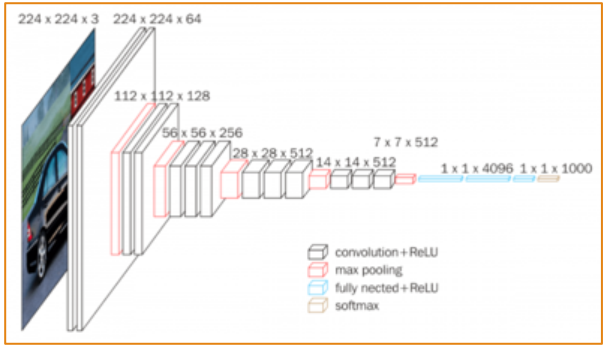
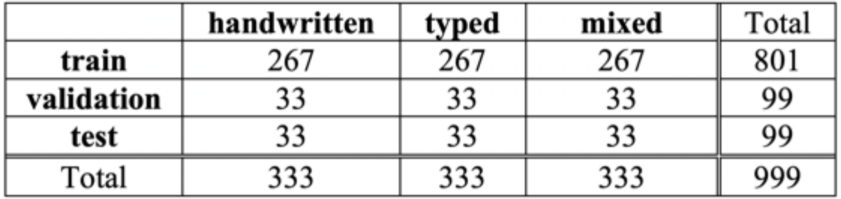


Figure 8. Architecture of original VGG-16. In our project, the last softmax layer is adjusted to have a shape of 3, which is the number of our target classes; handwritten, typed, and mixed

Afzal, M. Z., Kölsch, A., Ahmed, S., & Liwicki, M. (2017, November). Cutting the error by half: Investigation of very deep CNN and advanced training strategies for document image classification. In *2017 14th IAPR International Conference on Document Analysis and Recognition (ICDAR)*(Vol. 1, pp. 883-888). IEEE.

# Document Type Classification | Datasets

- We have two datasets:
  - Experiment 1: *RVL-CDIP* (400,000 document images with 16 different balanced classes); publicly available
  - Experiment 2: *suffrage_1002* (1,002 document images with 3 different balanced classes); manually compiled from ***By the People: Suffrage*** campaign (Table 1)



| | **handwritten** | **typed** | **mixed** | Total |
|---|---|---|---|---|
| **train** | 267 | 267 | 267 | 801 |
| **validation** | 33 | 33 | 33 | 99 |
| **test** | 33 | 33 | 33 | 99 |
| Total | 333 | 333 | 333 | 999 |

Table 1. Configuration of *suffrage_1002* dataset.

Figure 9. Example document images from each 16 different classes

# Document Type Classification | Datasets

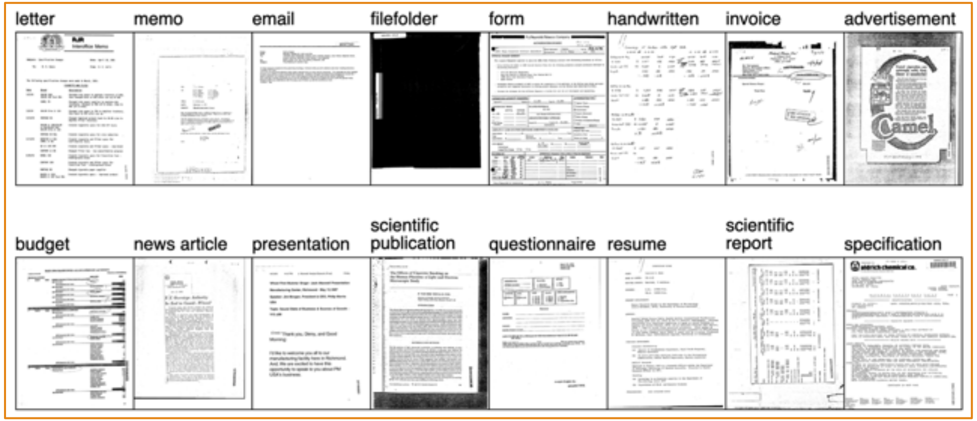


Figure 9. Example document images from each 16 different classes in *RVL_CDIP* dataset

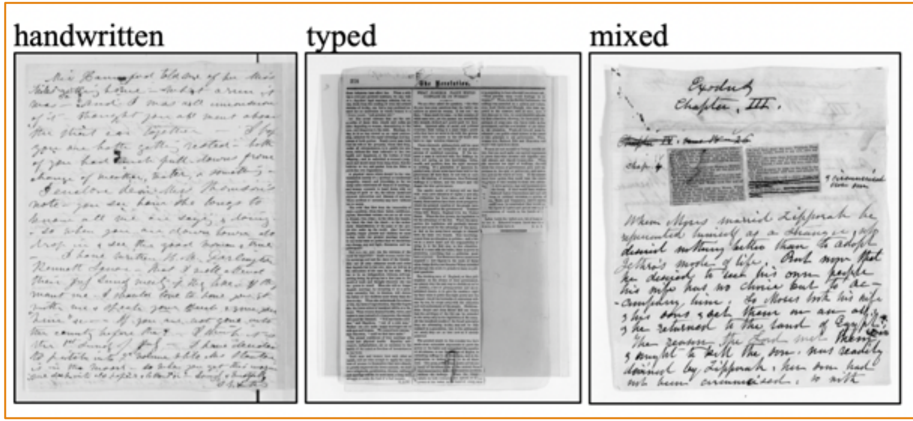


Figure 10. Example document images from each 3 different classes in *suffrage_1002* dataset

# Document Type Classification | Experimental Results

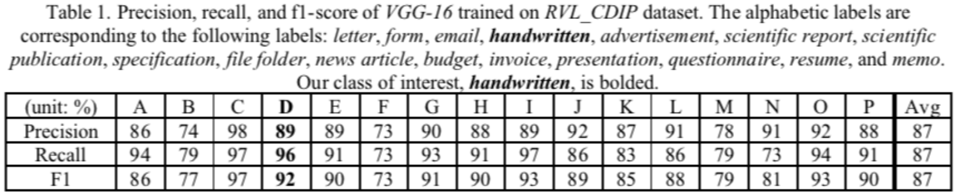


Table 1. Precision, recall, and f1-score of *VGG-16* trained on *RVL_CDIP* dataset. The alphabetic labels are corresponding to the following labels: *letter*, *form*, *email*, ***handwritten***, *advertisement*, *scientific report*, *scientific publication*, *specification*, *file folder*, *news article*, *budget*, *invoice*, *presentation*, *questionnaire*, *resume*, and *memo*. Our class of interest, ***handwritten***, is bolded.

| (unit: %) | A | B | C | **D** | E | F | G | H | I | J | K | L | M | N | O | P | Avg |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Precision | 86 | 74 | 98 | **89** | 89 | 73 | 90 | 88 | 89 | 92 | 87 | 91 | 78 | 91 | 92 | 88 | 87 |
| Recall | 94 | 79 | 97 | **96** | 91 | 73 | 93 | 91 | 97 | 86 | 83 | 86 | 79 | 73 | 94 | 91 | 87 |
| F1 | 86 | 77 | 97 | **92** | 90 | 73 | 91 | 90 | 93 | 89 | 85 | 88 | 79 | 81 | 93 | 90 | 87 |

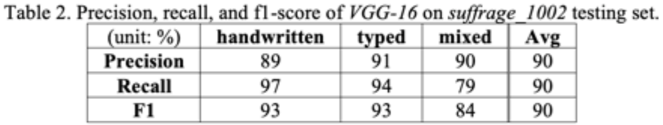


Table 2. Precision, recall, and f1-score of *VGG-16* on *suffrage_1002* testing set.

| (unit: %) | **handwritten** | **typed** | **mixed** | **Avg** |
|---|---|---|---|---|
| **Precision** | 89 | 91 | 90 | 90 |
| **Recall** | 97 | 94 | 79 | 90 |
| **F1** | 93 | 93 | 84 | 90 |

- ❑ Experiment 1: We obtained a model trained on a large-scale document image dataset, *RVL-CDIP* with promising classification performance, as shown in Table 1
  - ❑ ***Implication***: Features learned from natural images (ImageNet) are general enough to apply to document images
  - ❑ Now we can utilize this model by retraining it with our own *suffrage_1002* dataset in Experiment 2
- ❑ Experiment 2: The retrained model shows even better classification performance, as shown in Table 2

# Document Type Classification | Conclusions

- In both experiments, the state-of-the-art CNN model is capable of classifying document images with promising performance
  - ***Potential Applications***: help tagging an image type
- A main *challenge*: classifying a mixed type document image, as shown in Figure 11
  - ***Future Work:*** Perform a confidence level analysis to mitigate this problem
- ***Future Work:*** We expect that the classification performance can be further improved with a larger large-scale dataset

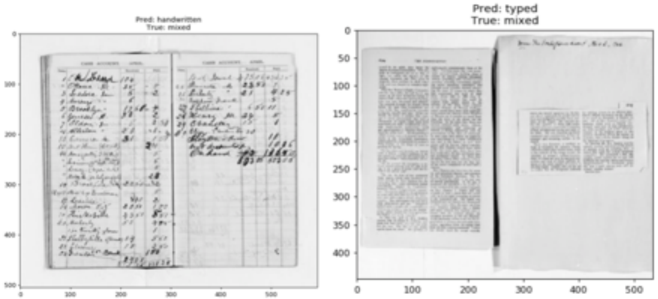

Pred: handwritten
True: mixed
0
100
200
300
400
500
0
100
200
300
400
500
Pred: typed
True: mixed
0
50
100
150
200
250
300
350
400
0
100
200
300
400
500

Figure 11. Failure prediction cases. On the left example, a typed region is relatively smaller than that of handwriting. On the right example, a handwriting region is relatively smaller than that of typing.

Afzal, M. Z., Kölsch, A., Ahmed, S., & Liwicki, M. (2017, November). Cutting the error by half: Investigation of very deep cnn and advanced training strategies for document image classification. In *2017 14th IAPR International Conference on Document Analysis and Recognition (ICDAR)*(Vol. 1, pp. 883-888). IEEE.

# Part 5: Library of Congress
# Project 4. Quality Assessment

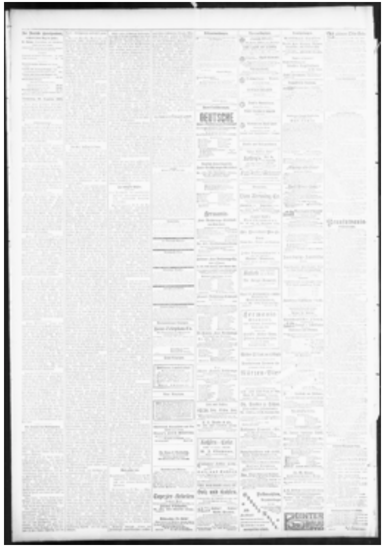
**Objectives** | Analyze image quality of  the civil war collection By the People

**Applications** | Providing quality scores for machine reading on four criteria: (1) *skewness*, (2) *contrast*, (3) *range-effect*, and (4) *bleed-through*

# Quality Assessment | Technical Details

- Objective quality assessment on four criteria
  - *Skewness, Contrast, Range-effect, Bleed-through*
  - *Based on the DIQA programs developed at Aida @ UNL (previously tested using Chronicling America's repository of archived newspaper pages*
  - *Not* directly machine learning related
- **Why**?
  - Help identify images that need pre-processing
  - Reduce unnecessary workload for pre-processing images
  - Indicate general qualities of the dataset

# Objective Quality Assessment | Examples



Contrast

Range-effect

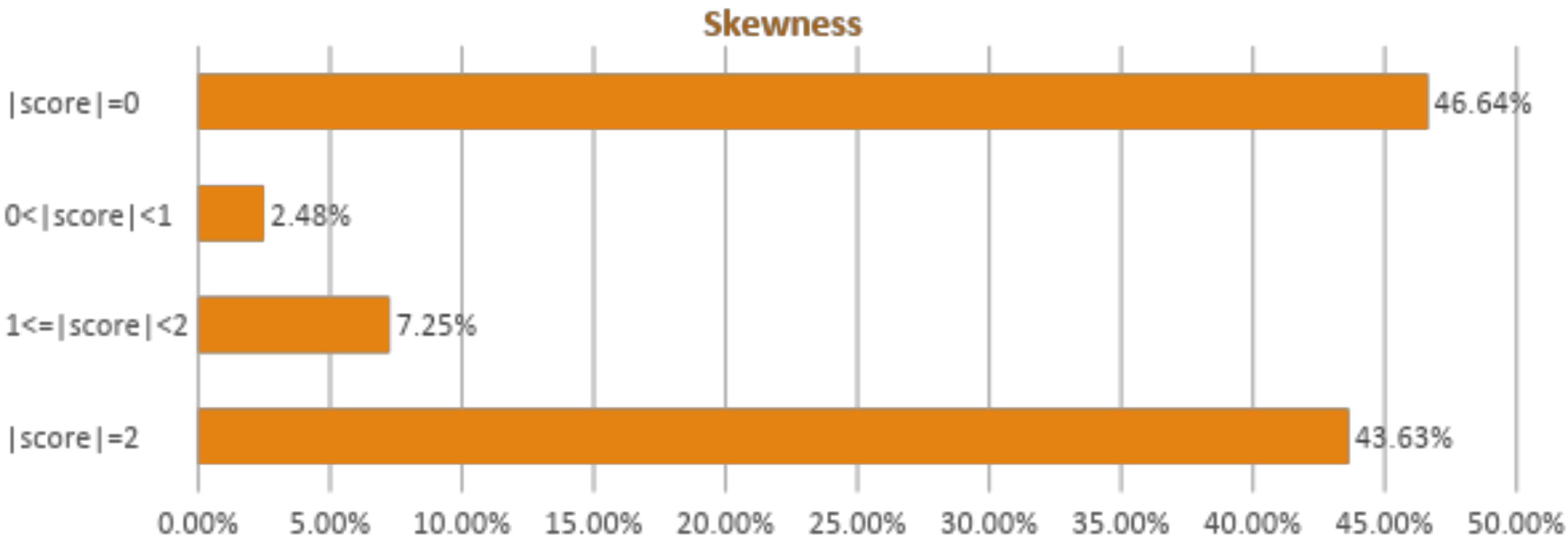
Bleed-through

Skewness

# Quality Assessment | Datasets

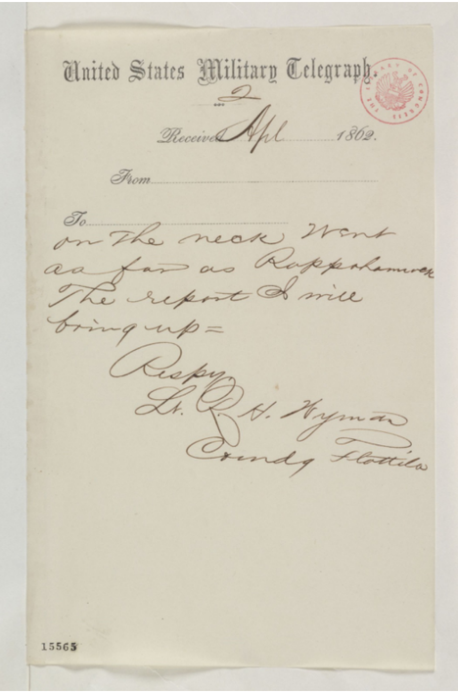
- The Civil War collection within By the People:
  - 36003 images were downloaded
  - 35990 images passed the DIQA program
    - *13 images failed as they barely had texts (see examples later)*

# Quality Assessment | Experimental Results



# Quality Assessment | Observations

- ❑ There were 46% images had the perfect score (zero) on skewness assessment
- ❑ But, there were also 43% images had the largest score (two)
- ❑ This suggest the skewness of the dataset may be divided
- ❑ However, a large portion of the dataset was hand-written
  - ❑ The skewness evaluation was depending on vertical aligned text line ends
  - ❑ Hand-written lines that were unjustified on left/right margin may result in a faulty score



United States Military Telegraph.

2

Received Apl 1862.

From

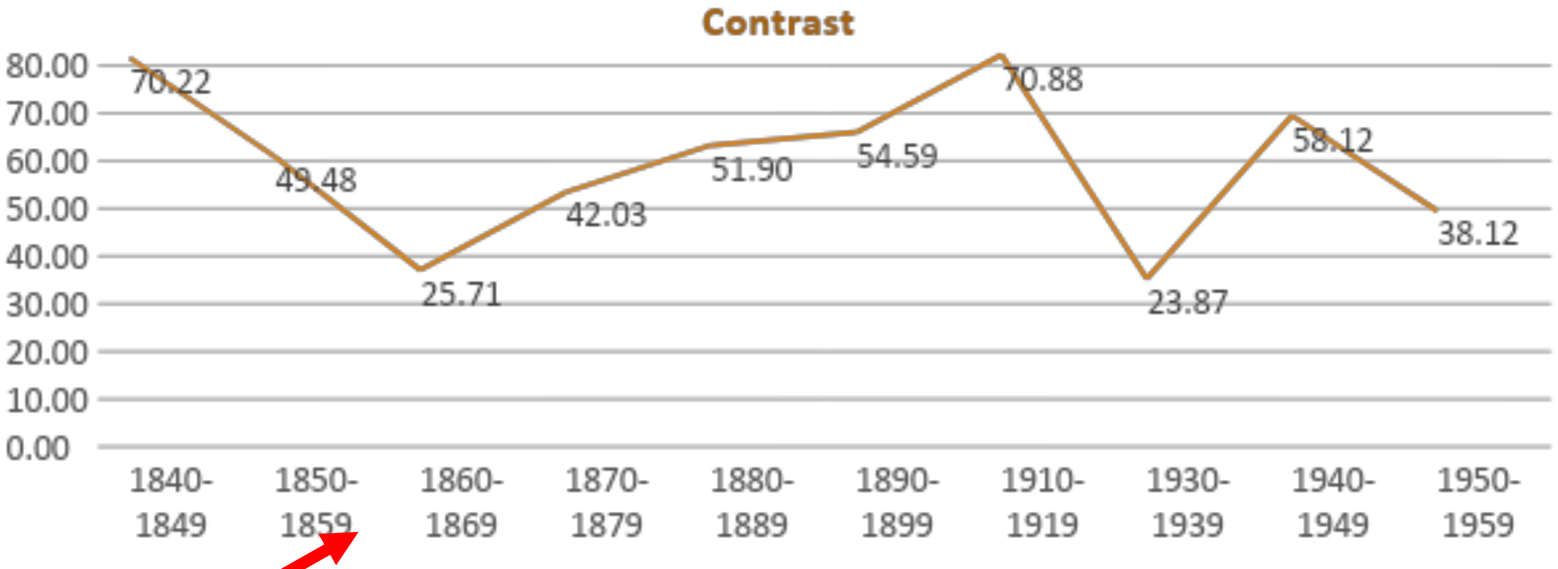
To

on the neck went
as far as Rappahannock
The report I will
bring up=

Respy
Lt. R. H. Hyman
Comdg Flottila

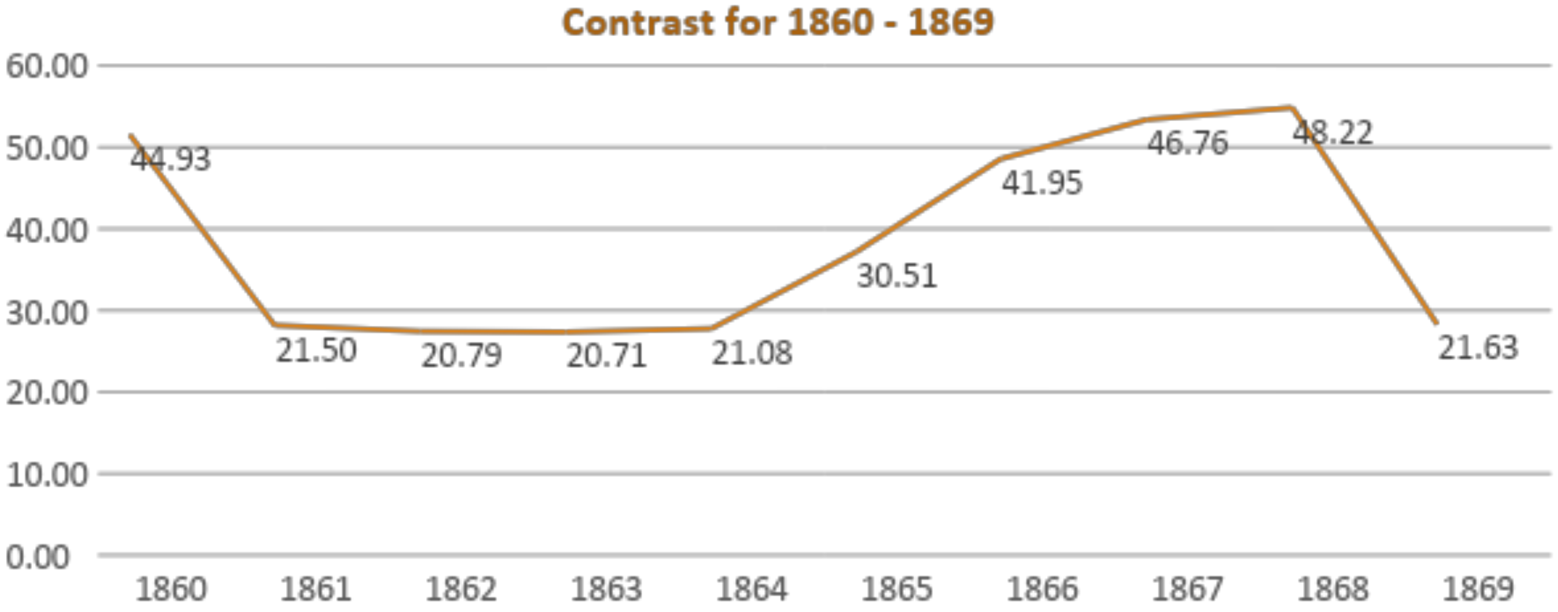
15565

# Quality Assessment | Experimental Results



~90% of images in the dataset falls within this range

# Quality Assessment | Experimental Results



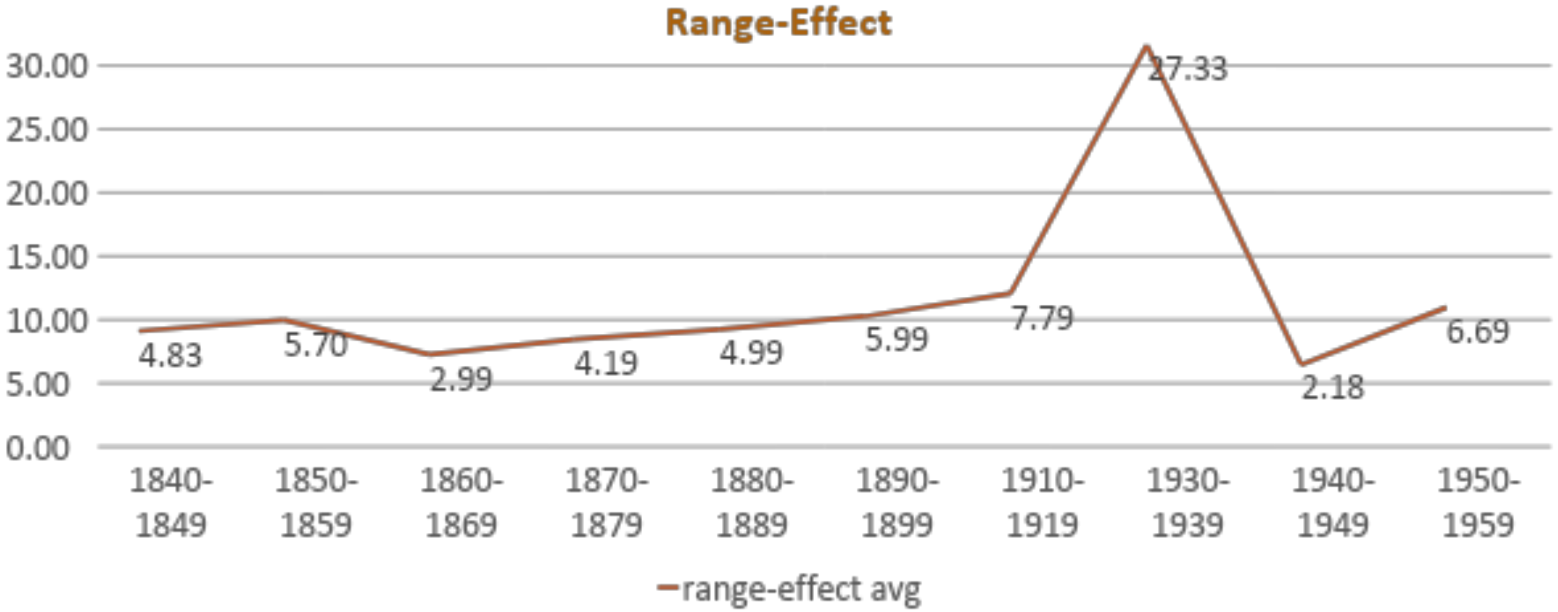
# Quality Assessment | Observations

- Based on previous work of Aida, contrast score less than 40 may cause troubles for reading

- The first chart shows the average contrast was good
- But ~90% images fall in year range from 1860 to 1869

- The second chart break the year range to year-wise analysis
- Images from 1961 to 1964 seem to have contrast issues

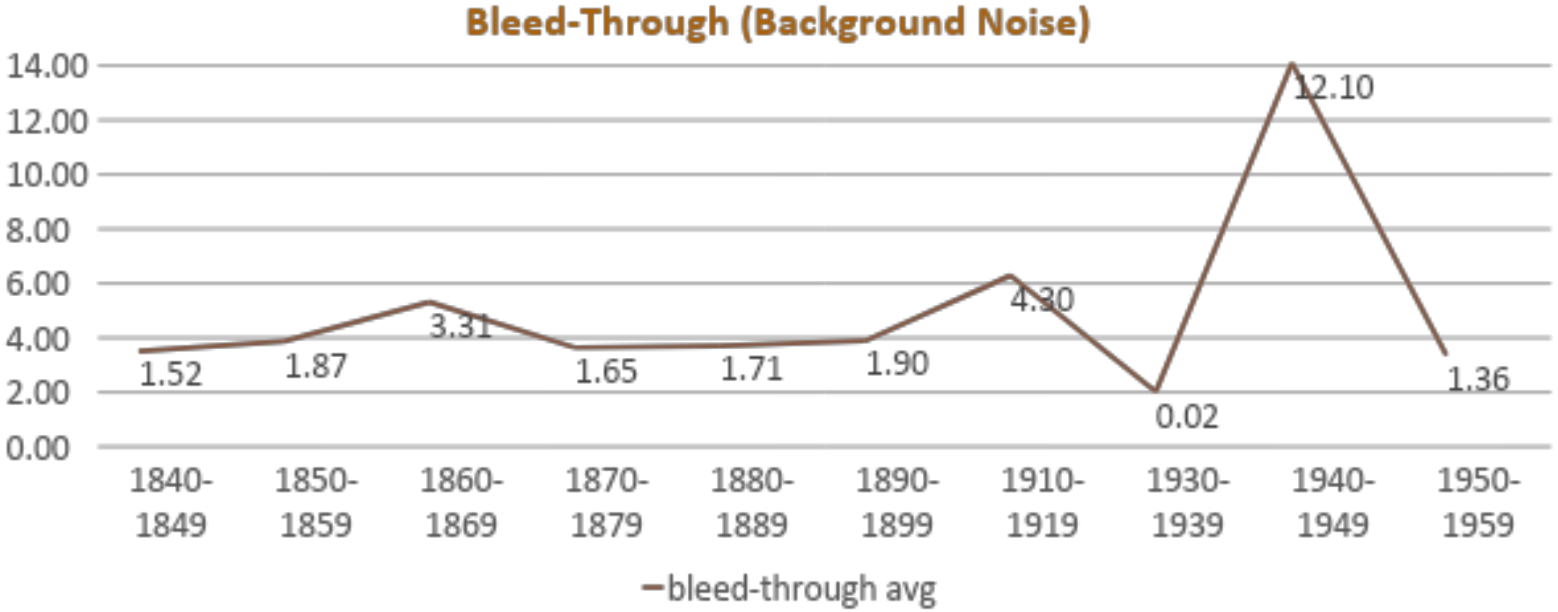
# Quality Assessment | Experimental Results



# Quality Assessment | Observations

- Based on DIQA on Chronicling America, range-effect score that is smaller than 3 is good
- Statistic data indicates the database averagely has quality issues on range effect

# Quality Assessment | Experimental Results



Aida

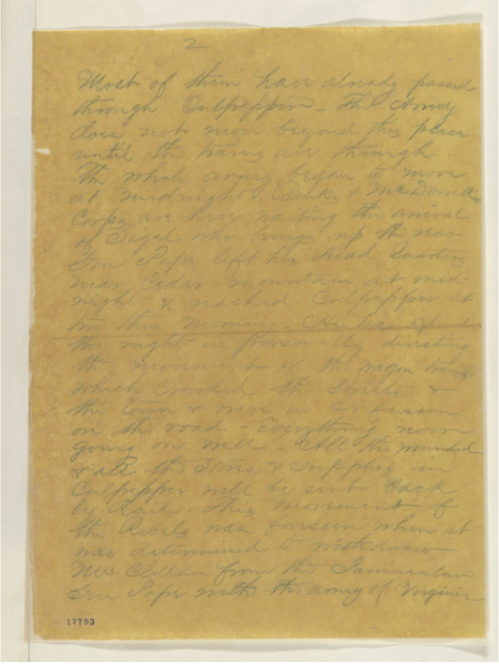
# Quality Assessment | Observations

- ❑ Unfortunately, there is no magic number to say which score is good
- ❑ But rather than 76 images from 1940 to 1949, other images has relatively lower score (better quality) on background noise

Aida

# Quality Assessment | Potential Issues

- ❑ Numerous images with yellowish background and faded inks
- ❑ They are hard to read even to human eye
  - ❑ Contrast could be lowered
  - ❑ Skewness could be almost impossible to compute



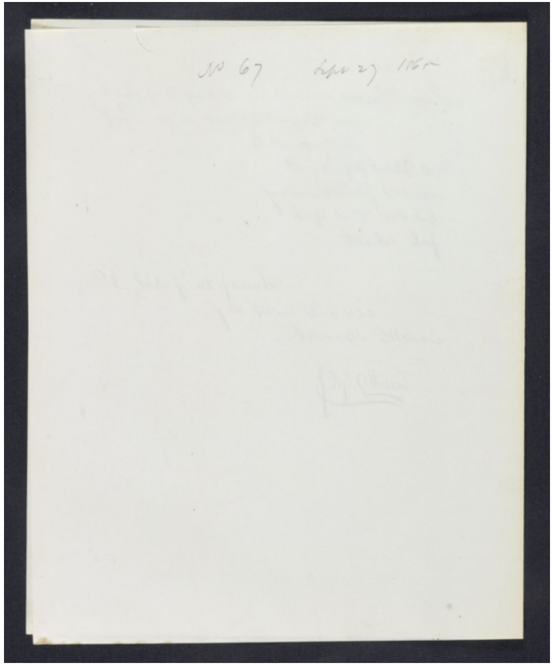
2

Most of them have already passed
through Culpepper – The Army
does not move beyond this place
until the trains are through.
The whole army began to move
at midnight. Banks & McDowells
Corps are here waiting the arrival
of Sigel who brings up the rear
Gen Pope left his Head Quarters
near Cedar mountain at mid-
night & reached Culpepper at
two this morning – He has spent
the night in personally directing
the movement of the wagon trains
which crowded the Streets &
the town & were in confusion
on the road – Everything now
going on well – All the wounded
& all the Stores & Supplies in
Culpepper will be sent back
by Rail. This movement of
the Rebels was foreseen when it
was determined to withdraw
McClellan from the Peninsula
Gen Pope with the army of Virginia

17793

# Quality Assessment | Potential Issues

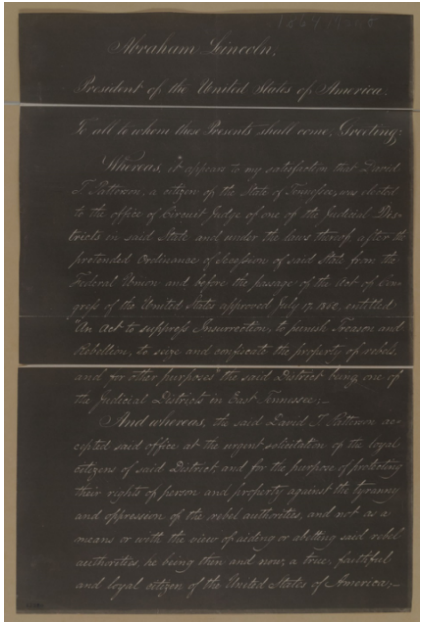
- ❑ Numerous images are covers or labels of a series
- ❑ These images are largely blank
  - ❑ Contrast is poor
  - ❑ Histogram equalization might be able to enhance the quality



No 67 Sept 27 1865

# Quality Assessment | Potential Issues

- ❑ There are color-inverted images from microfilm
  - ❑ Renders bleed-through assessment useless



Abraham Lincoln,

President of the United States of America.

To all to whom these Presents shall come, Greeting:

Whereas, it appears to my satisfaction that David T. Patterson, a citizen of the State of Tenneſsee, was elected to the office of Circuit Judge of one of the Judicial Districts in said State and under the laws thereof, after the pretended Ordinance of Seceſsion of said State from the Federal Union and before the passage of the Act of Congreſs of the United States approved July 17, 1862, entitled "An Act to suppreſs Insurrection, to punish Treason and Rebellion, to seize and confiscate the property of rebels, and for other purposes" the said District being one of the Judicial Districts in East Tennessee;—

And whereas, the said David T. Patterson accepted said office at the urgent solicitation of the loyal citizens of said District, and for the purpose of protecting their rights of person and property against the tyranny and oppression of the rebel authorities, and not as a means or with the view of aiding or abetting said rebel authorities, he being then and now, a true, faithful and loyal citizen of the United States of America;—

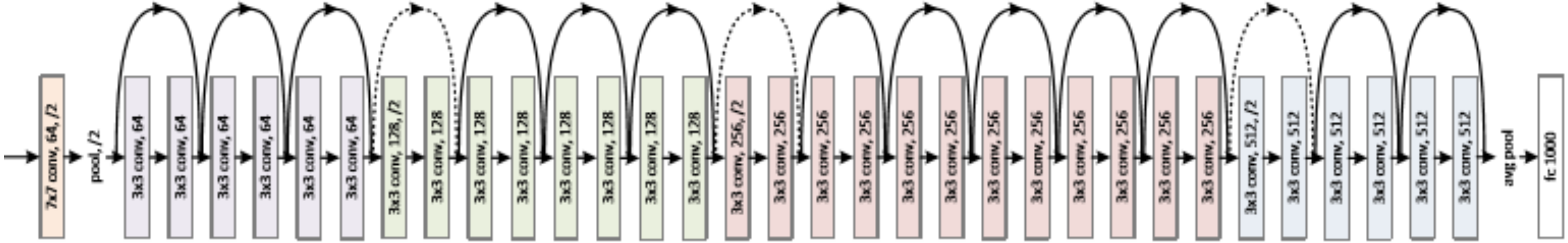
# Part 5: Library of Congress
# Project 5. Digitization Type Differentiation: Microfilm or Scanned

**Objectives** | Recognize if an image digitized from *Scanned* or *Microfilm*

**Applications** | Metadata generation, pre-processing policy selection

# Digitization Type Differentiation | Technical Details

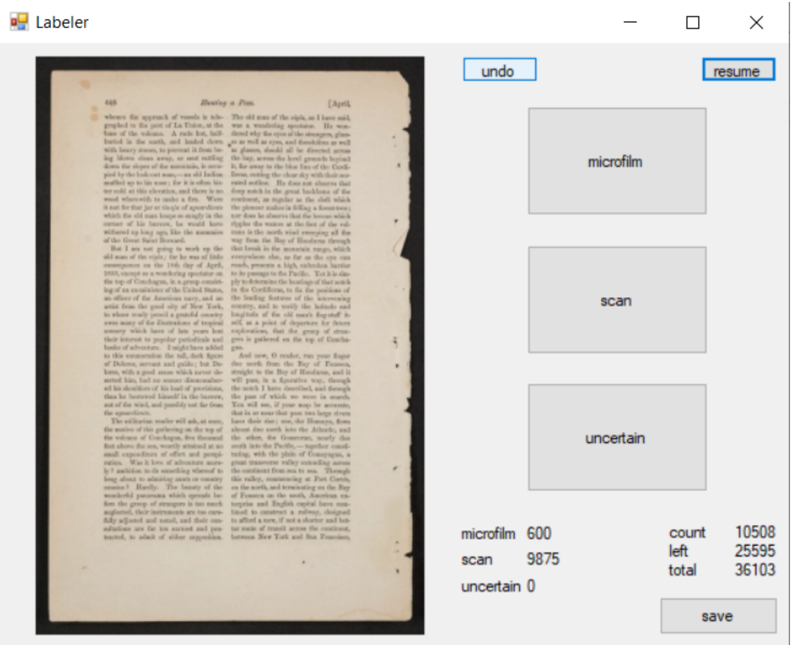
- Pre-trained ResNeXt is adopted
- Attached output layers are two dense layers with a 1D output vector
- **The pre-trained ResNeXt can classify images to 1000 different categories**
- The pre-trained ResNeXt is a good feature extractor
  - Number of parameters: 94.1 million ⍰ 12.6 million



# Digitization Type Differentiation | Datasets

- Created from the Civil War collection within By the People
- A manually created database by ***randomly*** choosing 600 images on scanned materials and 600 images on microfilm materials
- The randomization was performed by shuffling the entire list of 36,003 images in the collection
- The randomization ensured that images in the collection have a fair chance to be chosen
- The randomization seed was fixed to ensure the experiments can be reproduced

# Digitization Type Differentiation | Datasets



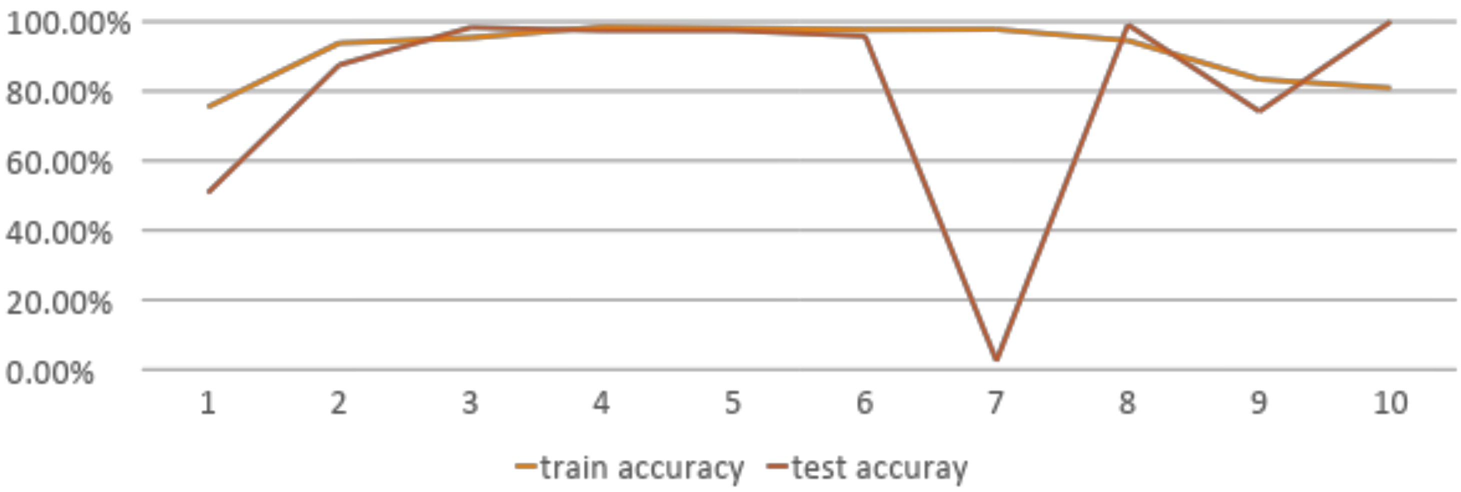
microfilm 600
scan 9875
uncertain 0

count 10508
left 25595
total 36103

- ❑ **Rough estimate**: Based on 10,508 images that was processed, ***ratio of images from microfilm to scanned materials is about 1:16***

# Digitization Type Differentiation | Experimental Results

- ❑ With pre-trained ResNeXt,
  - ❑ It only took **one** iteration to reach more than 90% accuracy on training set, and
  - ❑ It only took **two** iterations to reach more than 90% accuracy on testing set



# Digitization Type Differentiation | Experimental Results

- The best test iteration result was able to 100% correctly classify all images

| | | **Ground Truth** | |
|---|---|---|---|
| | | Scanned | Microfilm |
| **Prediction** | Scanned | 60 | 0 |
| | Microfilm | 0 | 60 |

# Digitization Type Differentiation | Conclusions

❑ Existing pre-trained model can be easily extended to more designated tasks

❑ The extended model only need a small set of labeled data to reach near-perfect performance in this task

❑ Automated digitization type differentiation is ***readily*** achievable.

# Questions?