europeana transcribe

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TOMORROW TODAY

ENRICHEUROPEANA+

An Approach for Curating Collections of Historical Documents with the Use of Topic Detection Technologies

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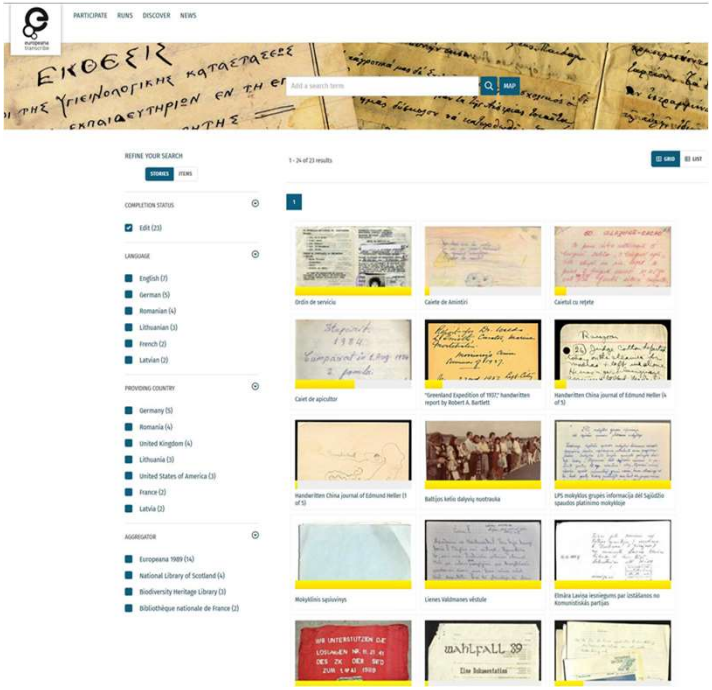
AGENDA

- Introduction
  - Transcribathon tool
- Motivation
  - Content curation for Transcribathon runs
- Proposed approach
  - Topic detection
  - Building LDA Models
  - Topic based information retrieval
- Experimental Evaluation
- Conclusions and Future Work

INTRODUCTION

Transcribathon

- A tool for transcription and enrichment of historical documents
- Using curated materials from Europeana collections

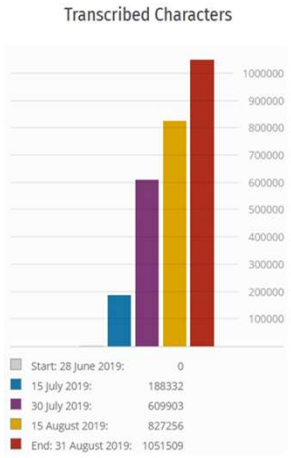


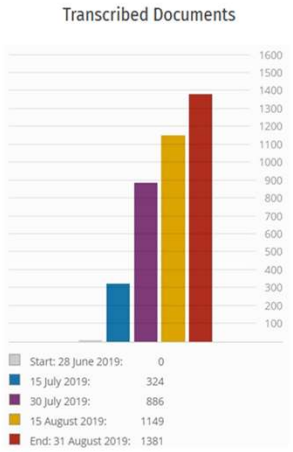
https://europeana.transcribathon.eu

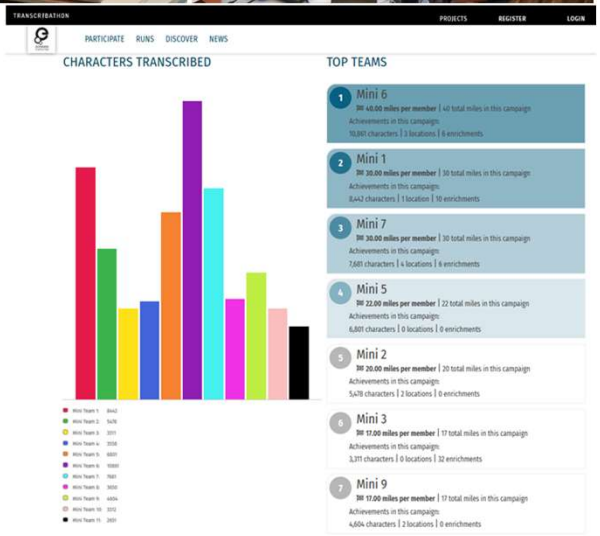
CROWDSOURCING CAMPAIGNS

Transcribathon = Transcription Marathon

- Physical, online or mixed competitions
- A gamification approach
- Focus on targeted audience







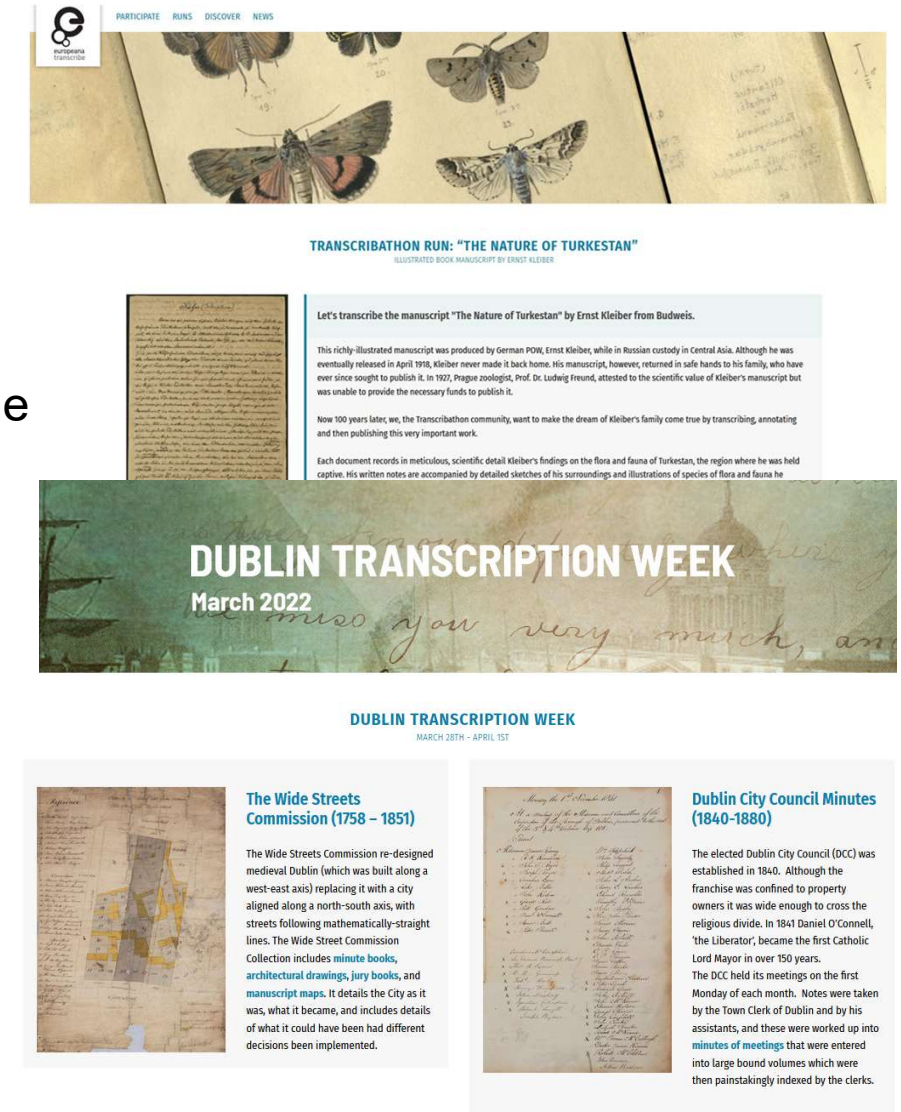
https://europeana.transcribathon.eu

THEMATIC RUNS

Curated materials on specific themes

- Memories from the First World War
- 1989 Revolution in Eastern Europe
- Industrial revolution
- Societal and urban development in the 19th century
- Also curated for local audiences
  - 20+ European Cities

https://europeana.transcribathon.eu



MOTIVATION

Automated support for curation activities

- Curate materials for Transcribathon themes
- Manual content curation is an expensive activity
- Domain expertise and knowledge in different languages is required

AI opportunities for CH

- Machine translation supported for all European languages
- Natural language processing and machine learning approaches available
  - Classification / clustering / recommendations / event prediction …

PROBLEM DESCRIPTION

Proposed Approach

- Use of topic detection technology to support digital curation activities
- Use unsupervised learning approach – LDA (Latent Dirichlet Allocation)

Goals:

- Organize materials available in the Transcribathon tool in several groups of closely related documents (group by topics)
- Implement efficient and scalable solutions for searching related content in Europeana (based on detected topics)

Challenges:

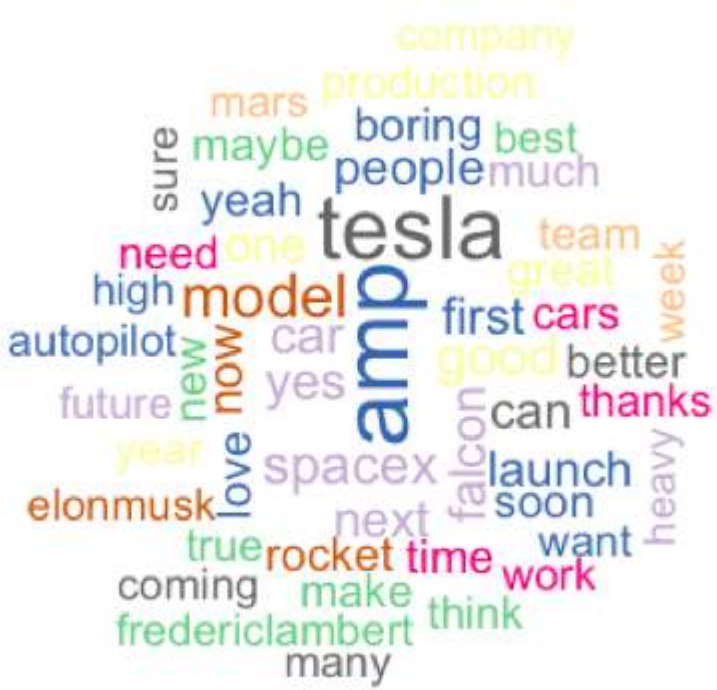
- Ensure appropriate and qualitative data for model learning
- Identify best-suited topic detection models
- Efficient implementation for topic-based search and categorization/clustering

TOPIC DETECTION

“Topic analysis (also called topic detection, topic modeling, or topic extraction) is a **machine learning technique that organizes and understands large collections of text data**, by assigning “tags” or categories according to each individual text's topic or theme.”

Source: https://monkeylearn.com/topic-analysis/

TOPIC DETECTION ON TWITTER



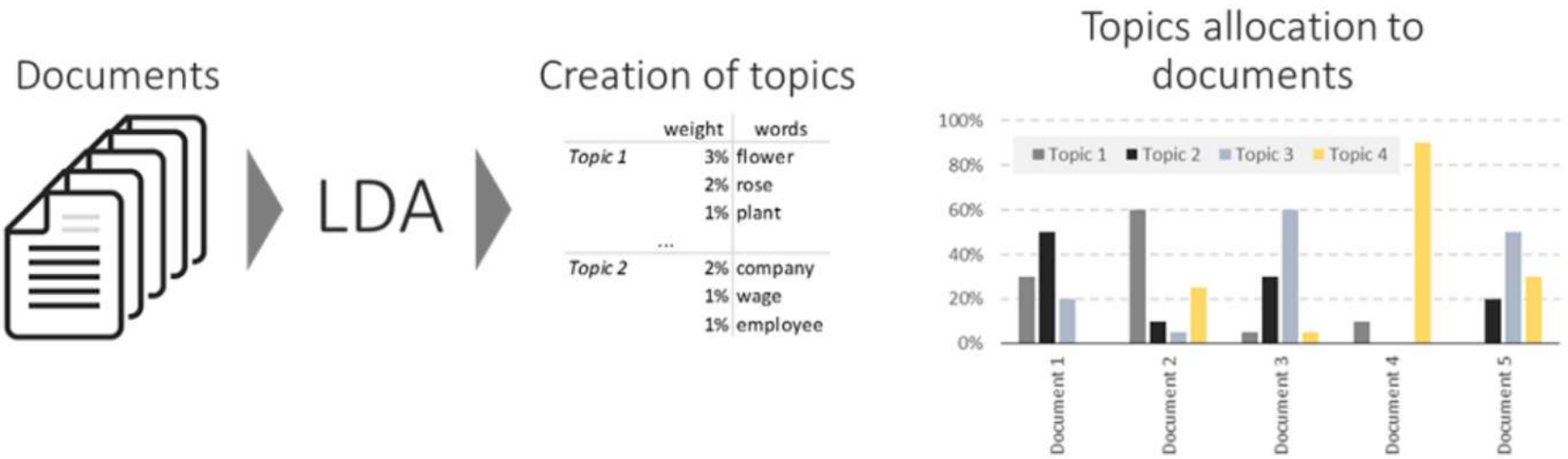
Word Cloud of Elon Musk's tweets

"Elon Musk uses his twitter account to talk about his work in **Tesla**, **The Boring Company**, and **SpaceX** as evident in this word cloud."

Source: https://towardsdatascience.com/elon-musk-twitter-adf324120b3f

TOPIC DETECTION - LDA

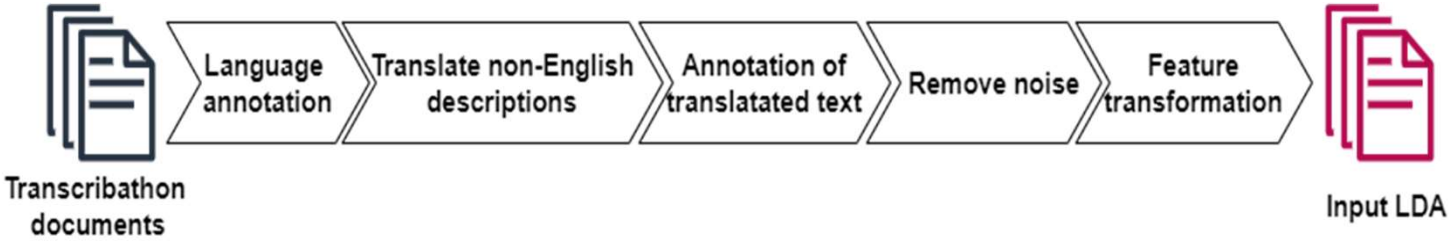
- LDA is one of the most popular unsupervised topic modelling methods
- Each document is made up of various words, and each topic also has various words (together with their weights) belonging to it. The aim of LDA is to find topics a document belongs to, based on the words in it.



Source: https://towardsdatascience.com/the-complete-guide-for-topics-extraction-in-python-a6aaa6cedbbc

LEARNING TOPIC MODELS

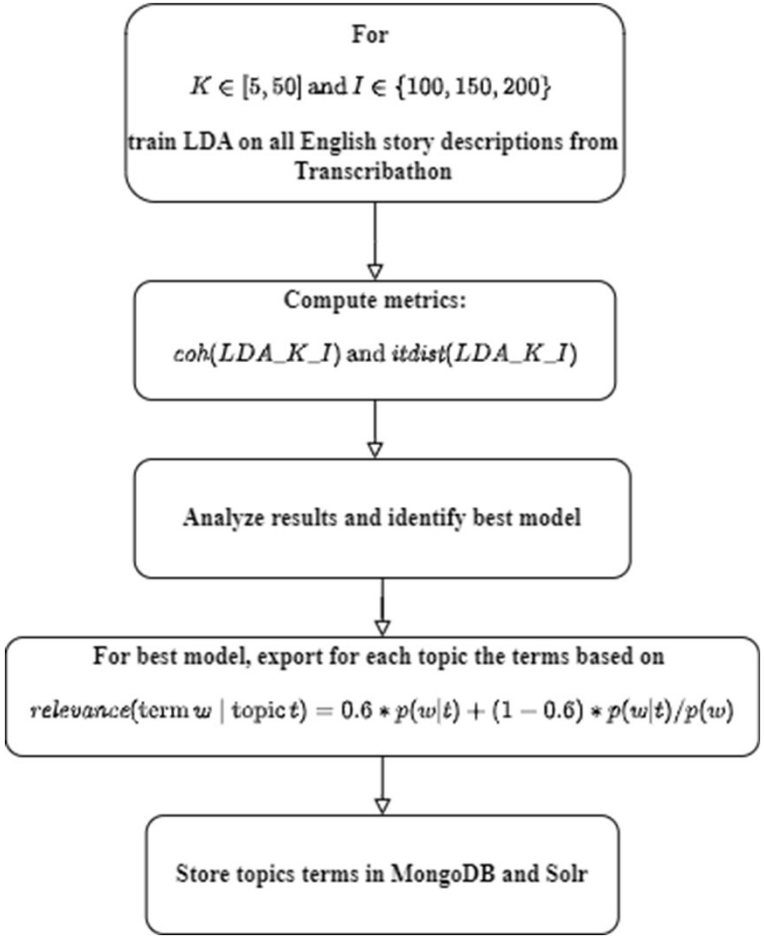
Pre-processing pipeline



Learning Topic Models

- LDA configuration paramerers: ***K*** – the number of topics to be learned,
  I – the number of iterations to run
- Which are the best LDA Models?
- Metrics for assessing the quality of the learned topics:
  - *Coherence* (Shaheen Syed, 2017)
  - *Inter-Topic Distance* (Carson S., 2014)

TOPIC MODEL SELECTION



1. Run LDA with different values for ***K*** and ***I***
2. Compute coherence and inter-topic distance metrics
3. Identify best model (expert intervention)
4. Export most representative topic terms and their relevancy
5. Store topics in the databases

TOPIC-BASED INFORMATION RETRIEVAL

Content curation from external repositories

- Topic assignment for new ingested materials
  - Supported directly by the LDA implementation

- Recommending new materials for a given Topic:
  - Retrieve candidate documents based on topic terms
  - Re-rank documents using the LDA Model
  - Build recommendation list

- How to ensure qualitative document recommendations?
  - Number of documents to search
  - Accuracy of recommendations list (Top N)

EXPERIMENTAL EVALUATION

Answering the following research questions:

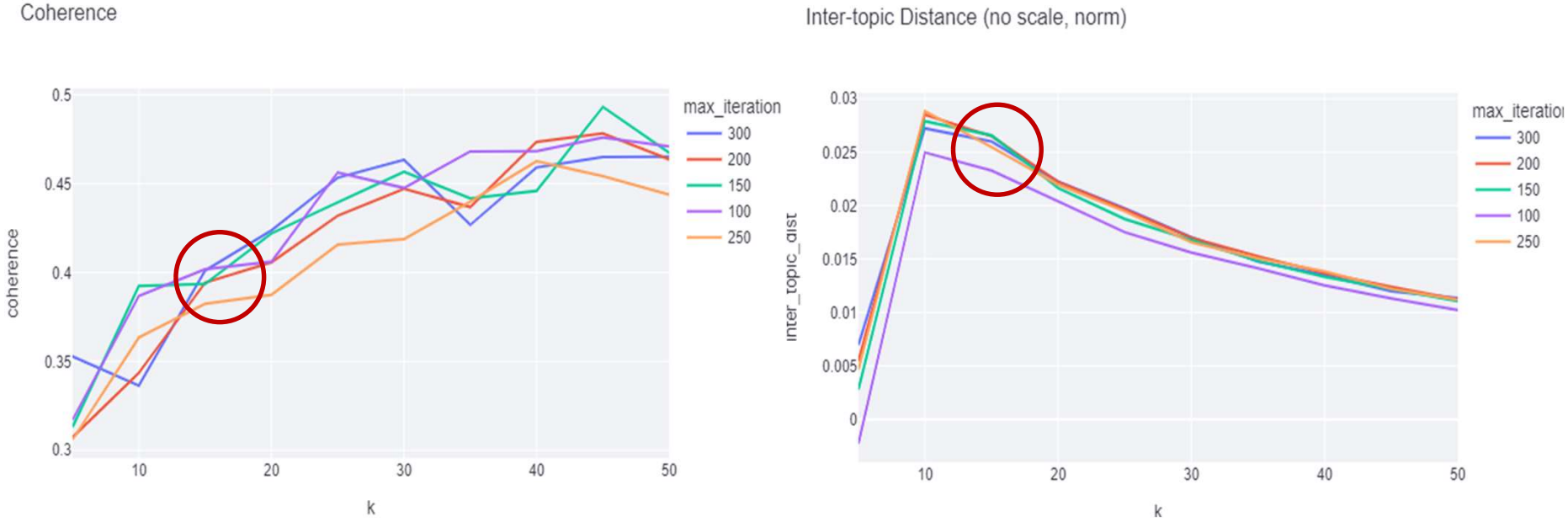
1. Which are the most appropriate ***K*** and ***I*** parameters for learning a good LDA Model on the complete Transcribathon dataset?

2. Which are the configurations required to obtain a good Precision at Top 10 (i.e., ***Precision@10***)?

Dataset:

- 31,957 documents available in Transcribathon (i.e. stories)
- Multilingual dataset (only a very small fraction have English description)
- ~ 28,000 words in vocabulary

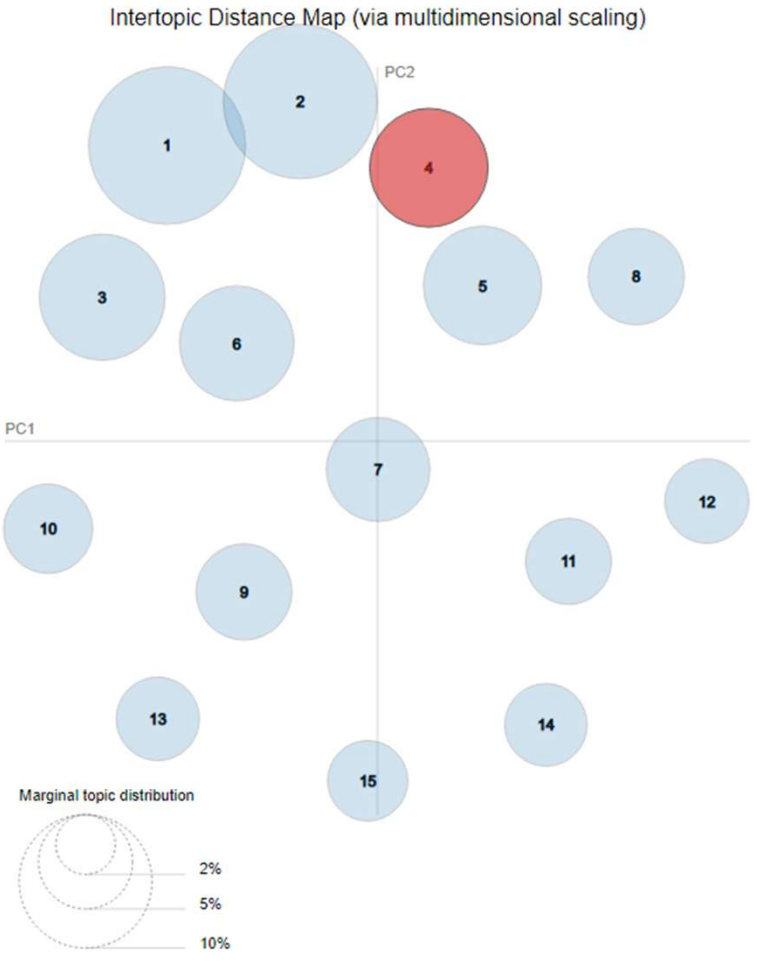
SELECTION OF MOST OPTIMAL LDA MODEL

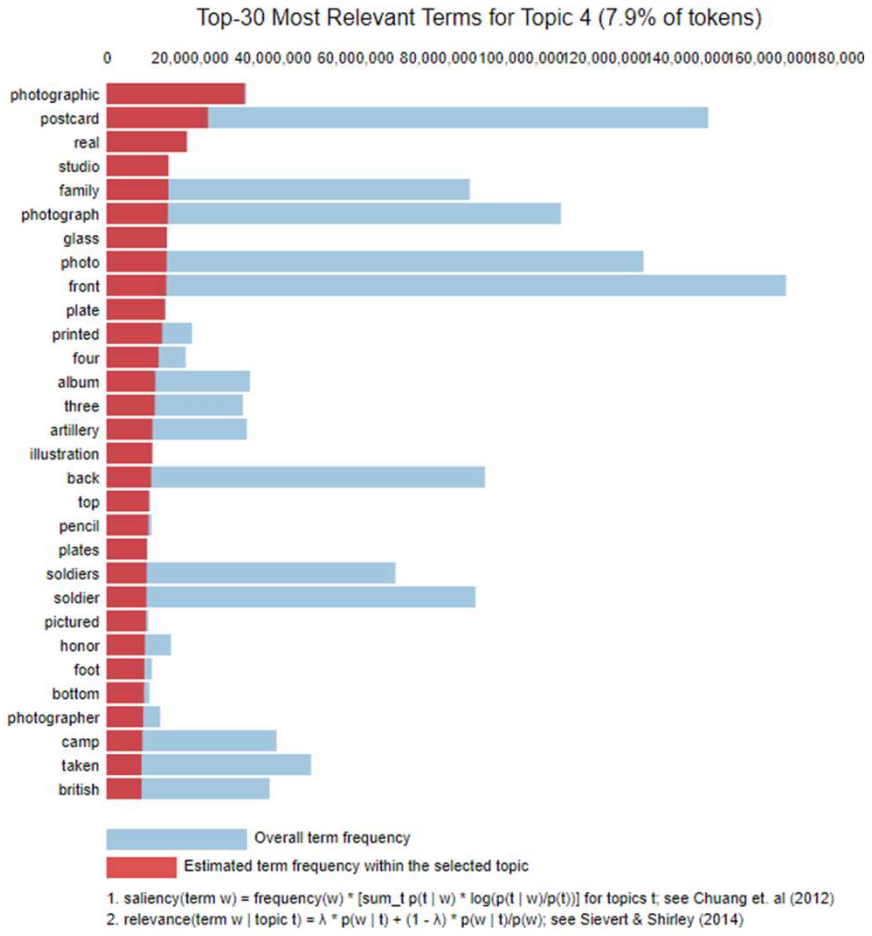


Observations:

1. Model training riches a saturation when ***I*** >= 150 (norm. inter topic distance)
2. Model overfitting for K > 25 (Coherence)
3. Performance for most of the models converges for ***K***=15 (similar performance of Models independent from I)
4. Most appropriate model for this dataset is considered ***LDA_15_150***

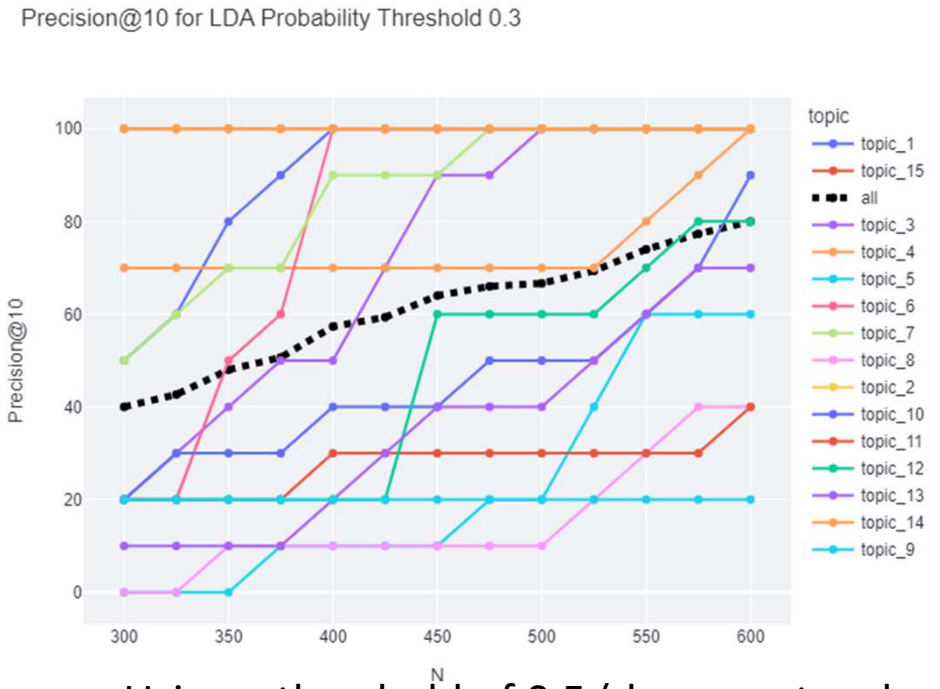
VISUALIZATION OF LDA MODELS

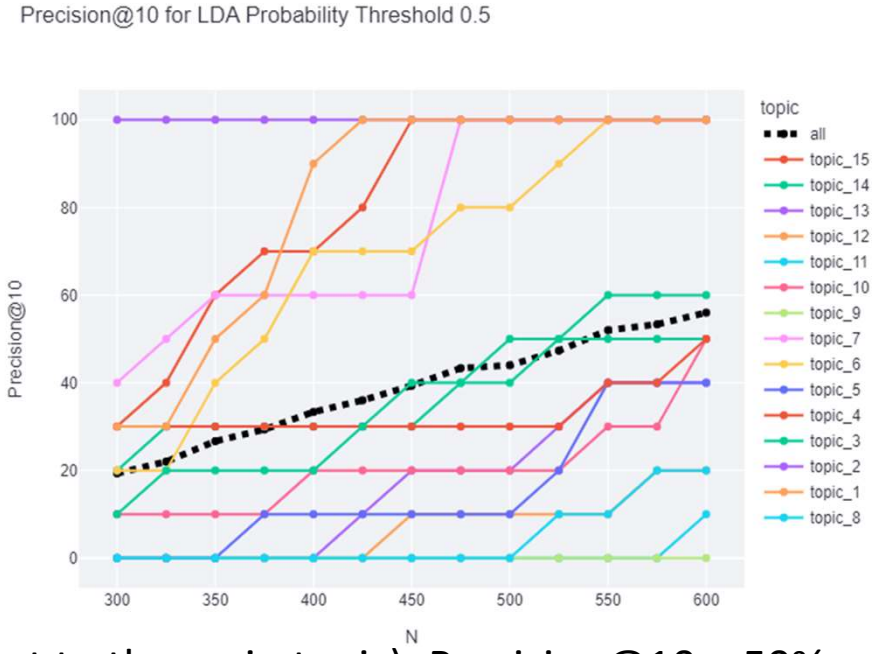




TOPIC-BASED CONTENT RECOMMENDATION

Precision@10 for different number of candidate documents - N and the relevant document thresholds of 0.3 and 0.5





- Using a threshold of 0.5 (documents relevant to the main topic): Precision@10 > 50% for N=550 (for N=600, Precision@10 = 56%).
- Using a threshold of 0.3 (documents relevant to their first and second topic) Precision@10 > 80% for N = 600 is obtained

CONCLUSIONS AND FUTURE WORK

- We propose:
  - Scalable approach for clustering large corpora of historical documents in finer grade collections.
  - Well-defined procedure for learning and choosing the best LDA topic model to support the curation of new materials for Transcribathon campaigns.
  - Search functionality from large CH repositories like Europeana to reduce the computation efforts required by LDA based document clustering.

- Future work:
  - Implementation of topic assignment for a given document using Solr
  - Investigation for using other topic modeling techniques such as BERTopic
  - Evaluate supervised machine learning approaches starting from the previously curated datasets

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THANK YOU!

Sergiu Gordea

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THEMES IN EUROPEANA 1914-1918