

Learning Equality - Curriculum Recommendations

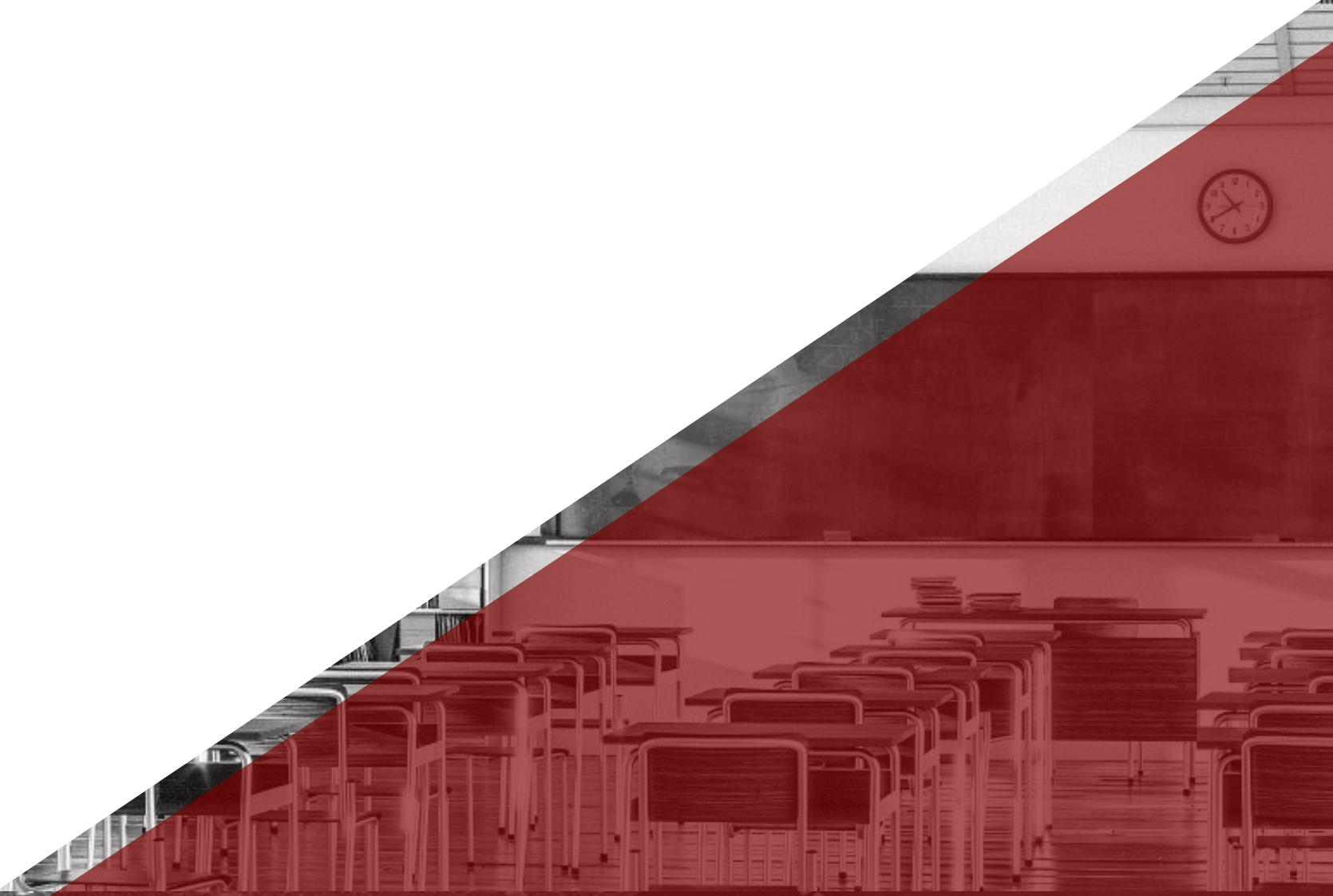
Enhance learning by matching K-12 content to target topics

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Agenda

- Problem Statement
- Prototype Solution
- Data Description
- EDA
- Feature Engineering
- Model Selection
- Conclusion
- Future Scope



Business Problem

Streamline the process of matching educational content to specific topics in a curriculum. We are developing an accurate and efficient model trained on a library of K-12 educational materials that have been organized into a variety of topic taxonomies. These materials are in diverse languages and cover a wide range of topics, particularly in STEM (Science, Technology, Engineering, and Mathematics).



Problem Statement

Demo App

Data Description

EDA

Solution Design

Model Selection

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Future Scope



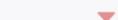
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X

Content Search

Select a topic

Dissolution of Partner



Description:

. this is the topic tree cbse >> cbse content -
final >> cbse >> elements of book keeping
and accountancy >> dissolution of
partnership firm >> dissolution of partner

Search

Learning Content Recommender

Search Results

Data Description

Topic

| Column | Description |
|-------------|---------------------------------|
| ID | Topic ID |
| Title | Title of the topic |
| Description | Description text |
| Channel | Topic Tree ID |
| Category | Origin of the topic |
| Language | Language of the topic |
| Parent ID | Parent ID of the topic |
| Level | The depth within its topic tree |
| Has Content | 1 if any content item is mapped |

Content

| Column | Description |
|-------------|--------------------------------|
| ID | Content ID |
| Title | Title of the content |
| Description | Summary of the content |
| Text | Full details about the content |
| Language | Language of the content |
| Kind | HTML, Document, Video, etc. |

Mapping

| Column | Description |
|-------------|-------------------------------|
| Topic ID | Topic ID |
| Content IDs | Related content for the topic |

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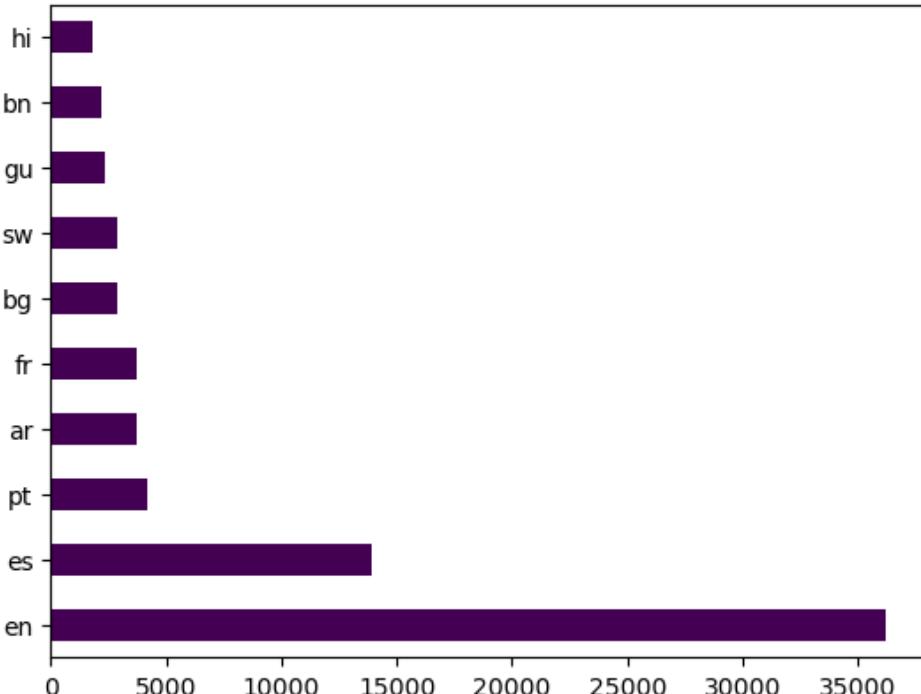
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Exploratory Data Analysis

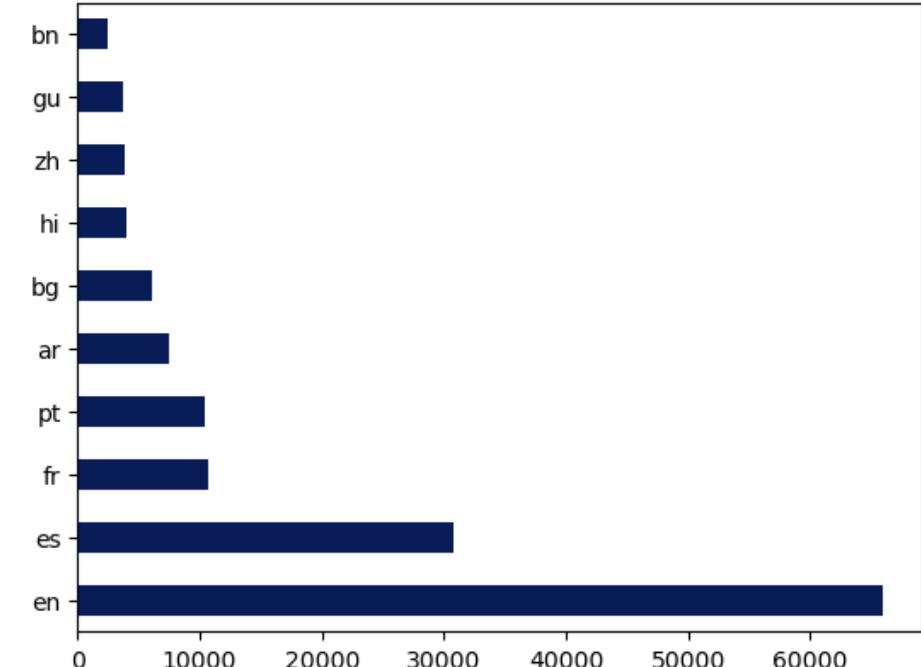
Most common languages of topics



The most common language for topics and contents is English, followed by Spanish.

An important thing to note is that the topics and contents must be of the same language to recommend.

Most common languages of contents



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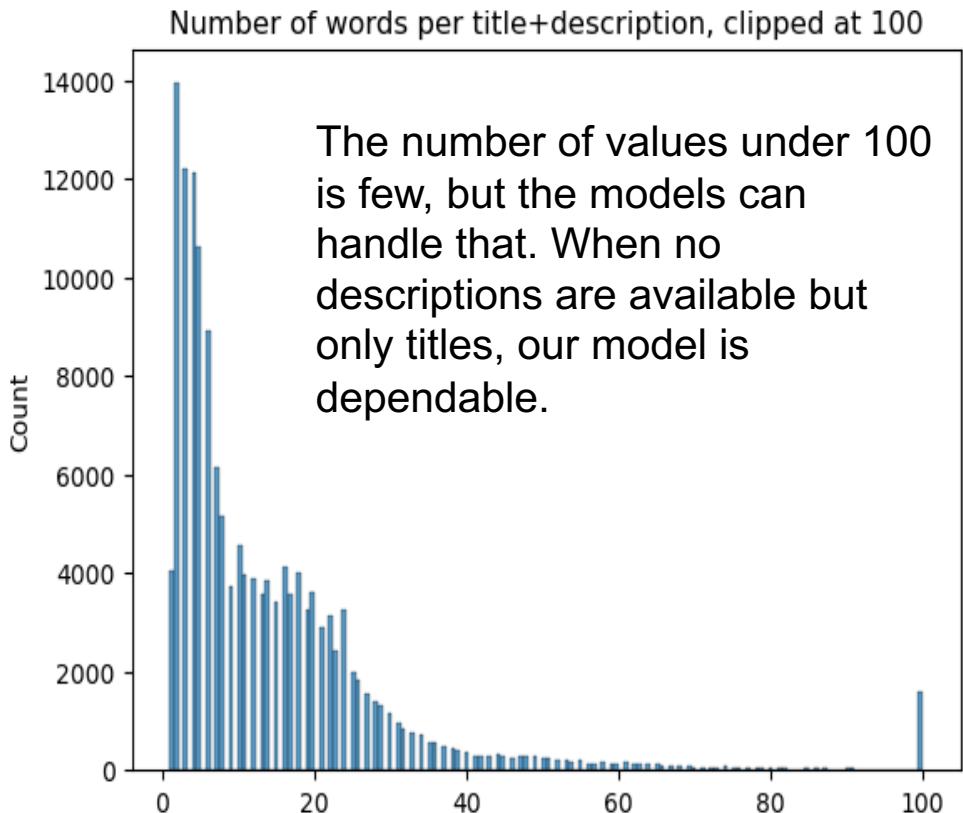
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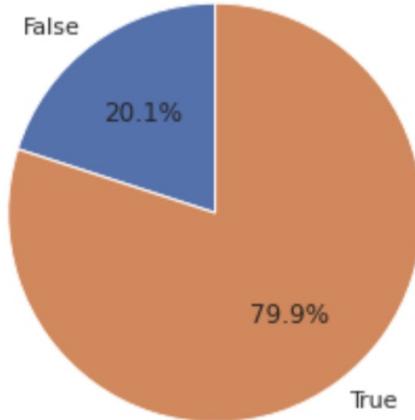


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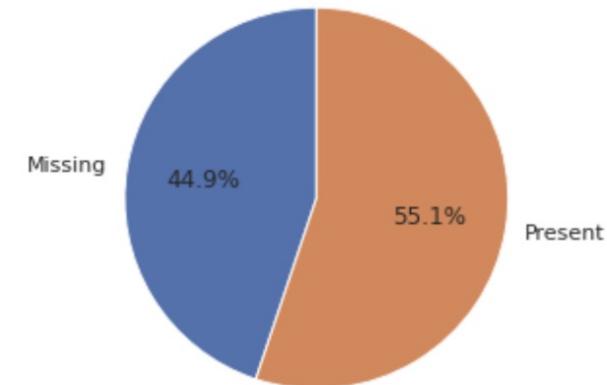
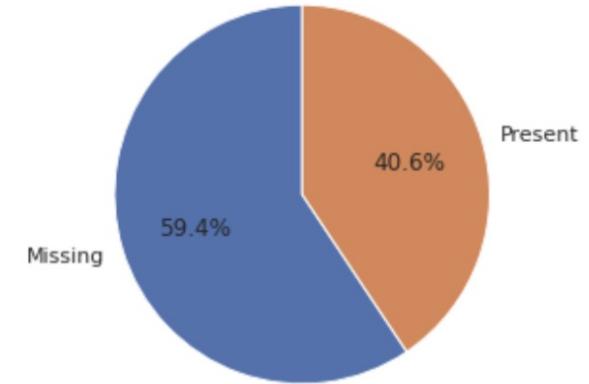
Exploratory Data Analysis



Name: has_content, dtype: int64



Num of content have text: 36347
Num of content don't have text: 29592



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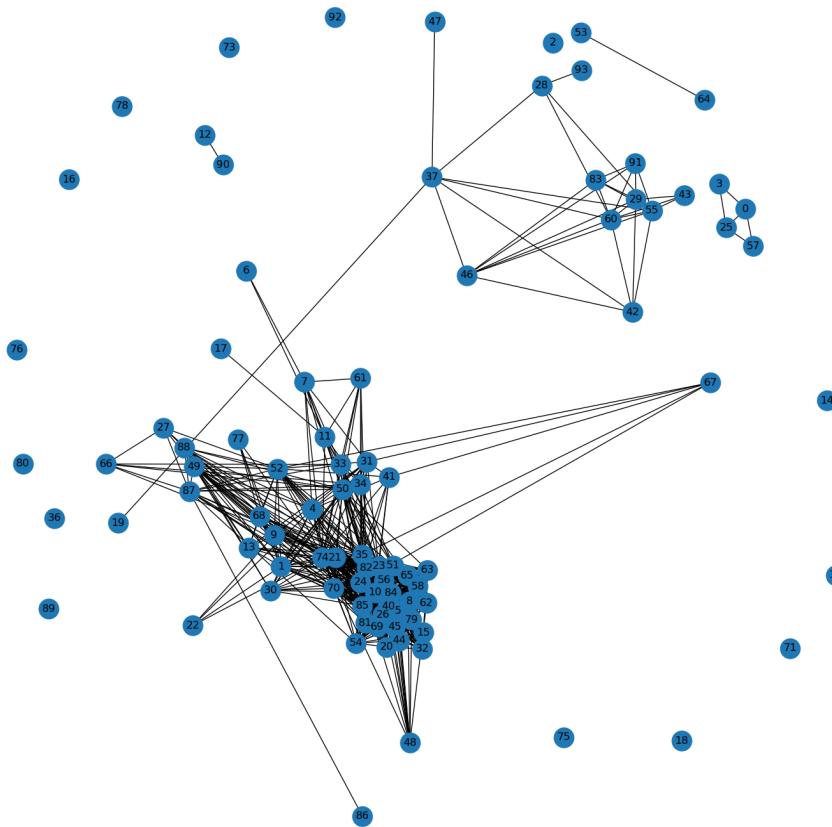
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Exploratory Data Analysis



Network graph
where the
channels are the
nodes, and the
content ids are
the edges

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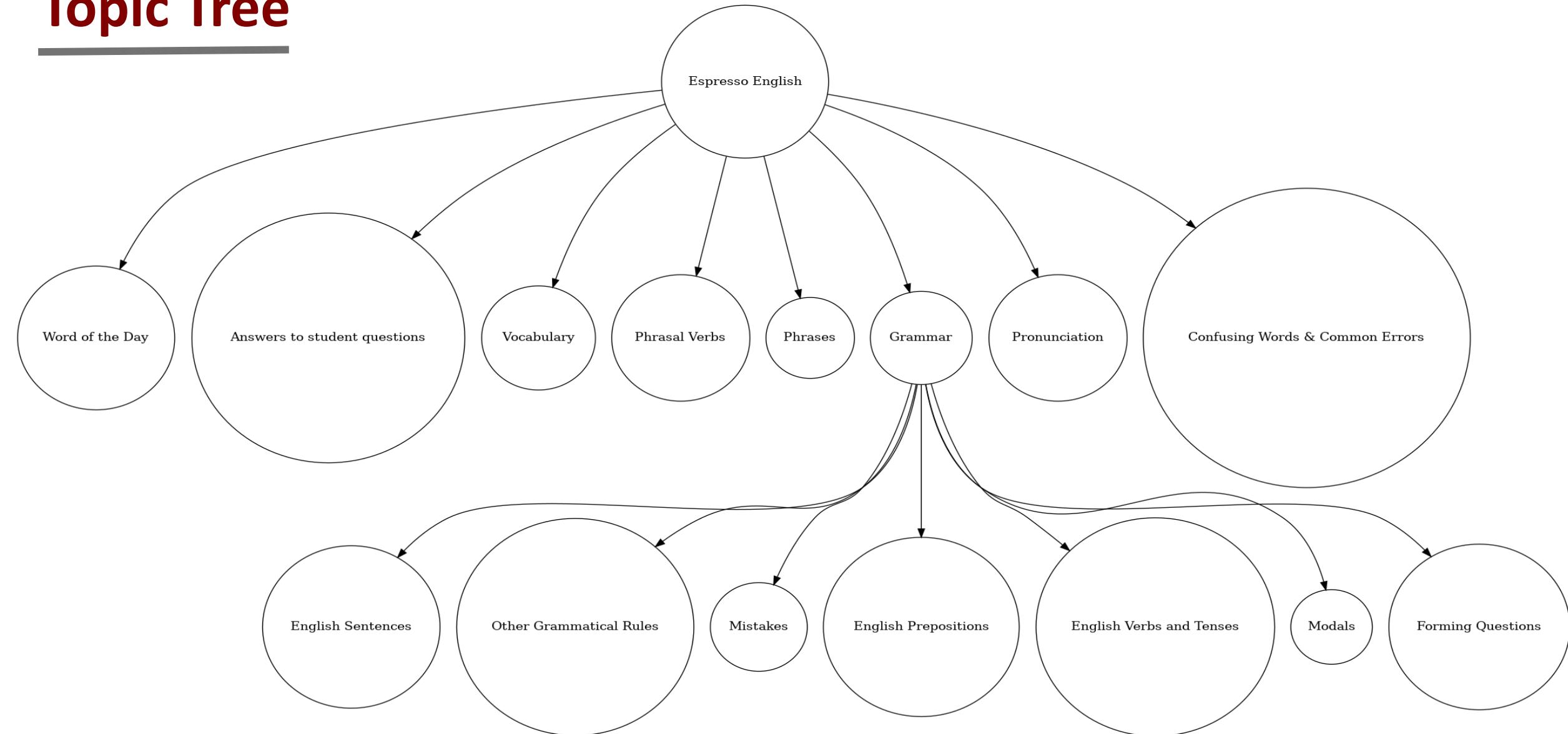
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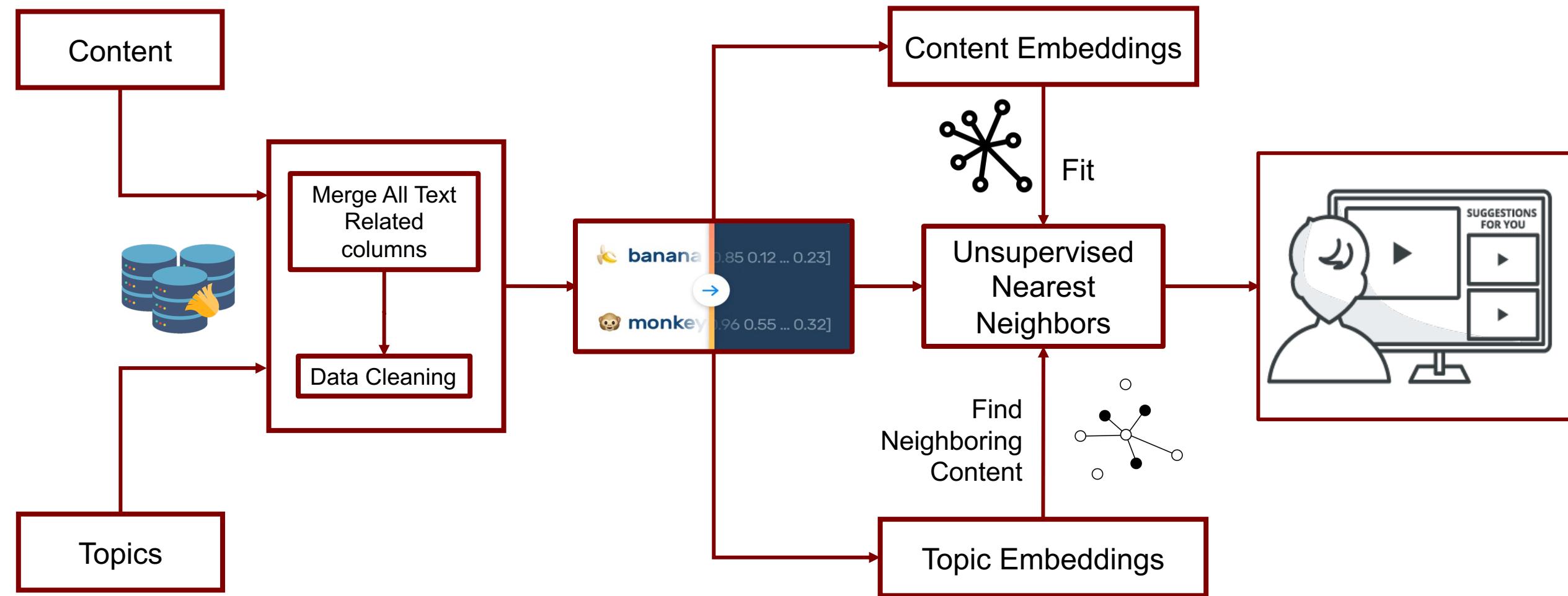


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Topic Tree



Solution Design



Model Selection

| Approach | Average F2 | Mean AP@ k |
|--|------------|------------|
| Count Vectorizer + Truncated SVD + Nearest Neighbors (Euclidean) | 0% | 0% |
| TF-IDF + Truncated SVD + Nearest Neighbors (Cosine) | 1% | 1.3% |
| Pre-Trained Model + Nearest Neighbors (Cosine) | 20.5% | 23% |

| Model Name | Performance Sentence Embeddings (14 Datasets) <small>i</small> | Performance Semantic Search (6 Datasets) <small>i</small> | Avg. Performance <small>i</small> | Speed <small>i</small> | Model Size <small>i</small> |
|--|--|---|-----------------------------------|------------------------|-----------------------------|
| paraphrase-MiniLM-L3-v2 <small>i</small> | 62.29 | 39.19 | 50.74 | 19000 | 61 MB |
| all-MiniLM-L6-v2 <small>i</small> | 68.06 | 49.54 | 58.80 | 14200 | 80 MB |
| multi-qa-MiniLM-L6-cos-v1 <small>i</small> | 64.33 | 51.83 | 58.08 | 14200 | 80 MB |
| paraphrase-multilingual-MiniLM-L12-v2 <small>i</small> | 64.25 | 39.19 | 51.72 | 7500 | 420 MB |
| all-MiniLM-L12-v2 <small>i</small> | 68.70 | 50.82 | 59.76 | 7500 | 120 MB |

Source: [SBERT](#)

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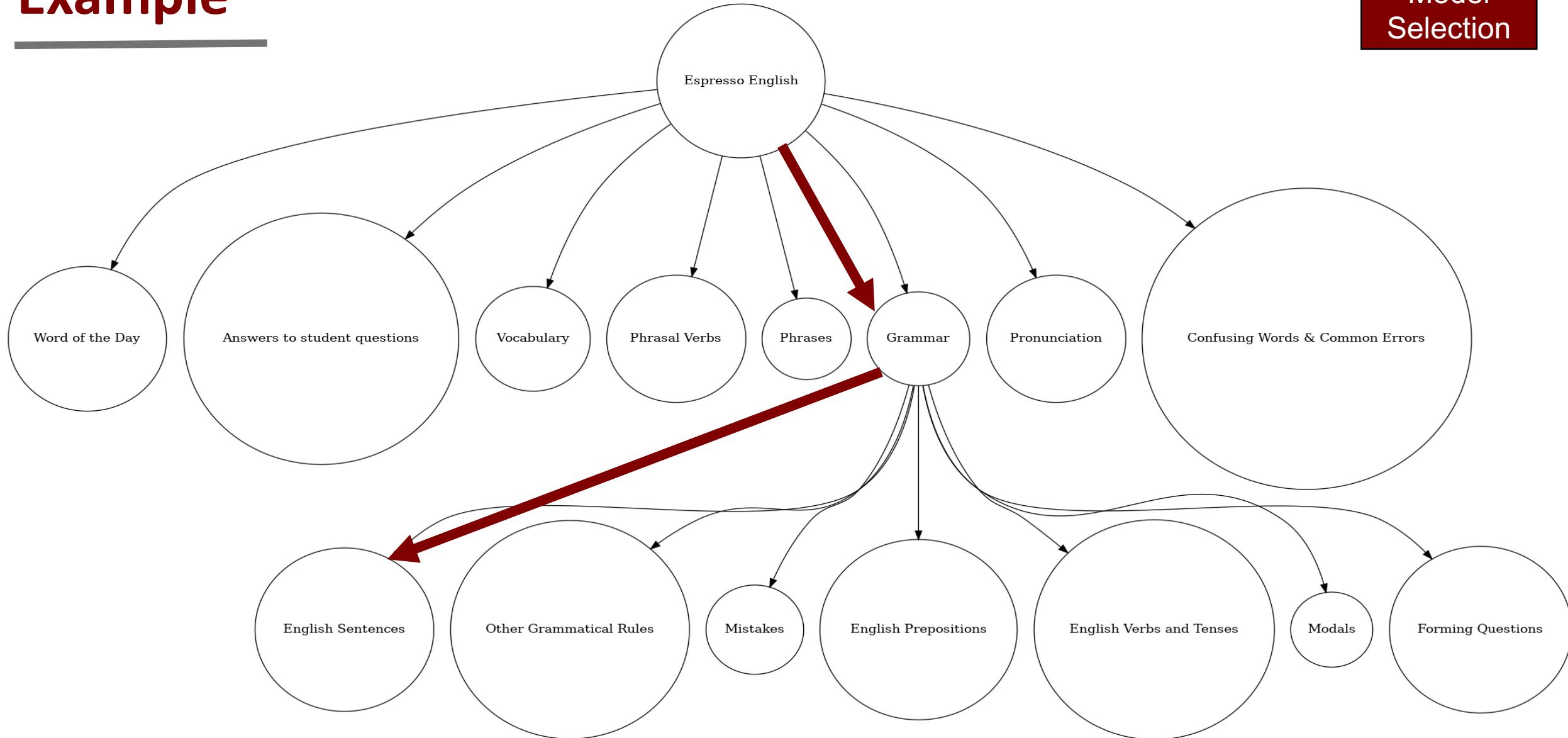
Future Scope



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Example

Model
Selection



Recommendation

| Current Content | Type of Content |
|--|-----------------|
| Sentence - Types and Structures | Video |
| How to form English sentences with NOT ONLY + BUT ALSO | Video |
| English Sentence Structure: 4 Types of English Sentences | Video |
| Recommended Content (Ranked by Similarity) | Type of Content |
| Sentence - Types and Structures | Video |
| GRAMMAR Modals (Part One) | Video |
| Subject Verb Object Sentences | Video |
| English Sentence Structure: 4 Types of English Sentences | Video |
| GRAMMAR Modals (Part Two) | Video |
| GRAMMAR Modals (Part Three) | Video |
| Subject and Object Questions in English | Video |

Topic Branch

Espresso English



Grammar



English
Sentences

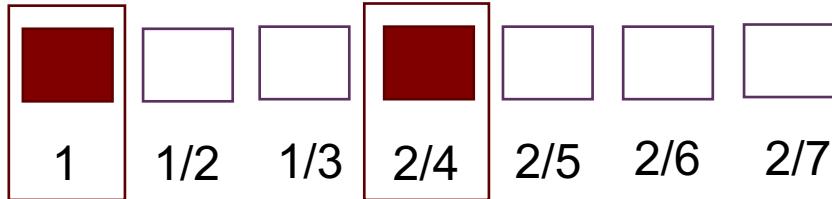
Evaluation

Average Precision @ K

Relevant Content



Recommended Content



$$\text{Average Precision @ K} = \frac{1 + 2/4}{2} = 75\%$$

$$\text{Mean Average Precision @ K} = \frac{\sum AP @ K}{\# \text{ of Topics}}$$

F2 Score

$$F2 \text{ Score} = \frac{TP}{TP + (0.2 * FP + 0.8 * FN)}$$

$$\text{True Positives} = 2$$

$$\text{False Positives} = 5$$

$$\text{False Negatives} = 1$$

$$F2 \text{ Score} = \frac{2}{2 + (0.2 * 5 + 0.8 * 1)} = 52.6\%$$

$$\text{Mean F2 Score} = \frac{\sum F2 \text{ Scores}}{\# \text{ of Topics}}$$

Conclusion

- ✓ Current efforts to align digital materials to national curriculum are manual and require time, resources, and curricular expertise, and the process needs to be made more efficient to be scalable and sustainable.
- ✓ As new materials become available, they require additional efforts to be realigned, resulting in a never-ending process.
- ✓ There are no current algorithms or other AI interventions that address the resource constraints associated with improving the process of curriculum alignment.

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Future Scope

- ❑ User feedback for recommendations and model improvement (collaborative filtering).
- ❑ Generating descriptions for the topics from their topic tree and then giving recommendations.
- ❑ Make our model multilingual.
- ❑ Retrain the model on pre-trained embeddings.
- ❑ Summarizing the topic description and content description.
- ❑ Add search engine feature on the app instead of drop down.

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**THANK YOU!
QUESTIONS?**

Appendix

| Model | Average F2 Score | Average Precision @k |
|----------------------------|------------------|----------------------|
| all-MiniLM-L6-v2 | 19.73 | 21.04 |
| multi-qa-mpnet-base-dot-v1 | 21.58 | 25.14 |
| paraphrase-MiniLM-L3-v2 | 12.20 | 11.93 |
| multi-qa-MiniLM-L6-cos-v1 | 20.45 | 21.97 |

With Description + Topic Tree

| Model | Average F2 Score | Average Precision @k |
|---------------------------|------------------|----------------------|
| all-MiniLM-L6-v2 | 14.22 | 15.30 |
| paraphrase-MiniLM-L3-v2 | 8.15 | 8.46 |
| multi-qa-MiniLM-L6-cos-v1 | 13.23 | 14.28 |

Only Topic Tree

This is a [sentence-transformers](#) model: It maps sentences & paragraphs to a [384 dimensional dense](#) vector space and can be used for tasks like clustering or semantic search.

multi-qa-mpnet-base-dot-v1

This is a [sentence-transformers](#) model: It maps sentences & paragraphs to a [768 dimensional dense](#) vector space and was designed for **semantic search**. It has been trained on 215M (question, answer) pairs from diverse sources. For an introduction to semantic search, have a look at: [SBERT.net - Semantic Search](#)

sentence-transformers/paraphrase-MiniLM-L3-v2

This is a [sentence-transformers](#) model: It maps sentences & paragraphs to a [384 dimensional dense](#) vector space and can be used for tasks like clustering or semantic search.

multi-qa-MiniLM-L6-cos-v1

This is a [sentence-transformers](#) model: It maps sentences & paragraphs to a [384 dimensional dense](#) vector space and was designed for **semantic search**. It has been trained on 215M (question, answer) pairs from diverse sources. For an introduction to semantic search, have a look at: [SBERT.net - Semantic Search](#)