

Generating Effective Headlines for Social Media Posts

Raymond Hung, Jack Forlines, Dipika Kumar

DATASCI 266: Natural Language Processing with Deep Learning

UC Berkeley School of Information

Introduction

What problem are we trying to solve?

- Advanced large language models (LLMs) are extensively utilized for summarizing news articles and documents
- Summarizing social media content poses unique challenges due to the variability in text length and need for captivating headlines

Practical Applications

- **Title Generations:** Automated suggestion of titles derived from the body text
- **Existing Implementations:**
 - Gmail incorporates suggested titles for email composition
 - eBay utilizes automated title generation for its listings

Create a listing

Photos



Title

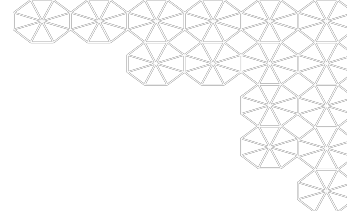
Powered by AI

2020 Panini Chronicles Justin Jefferson
Gridiron Kings Rookie Gem Mint 10

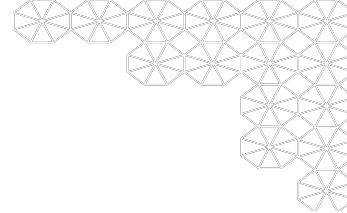
Source: [eBay's Magical Listing Tool](#)

Data

- **Reddit datasets:** Sourced from Kaggle containing 500K posts from data science and machine learning related subreddits
- **Data cleansed**
 - NAN rows removed
 - Text normalization
- **Added prefix, paired, shuffled, and produced 25K subset dataset**
 - 20K training (80%)
 - 3.75K validation (15%)
 - 1.25K test (5%)

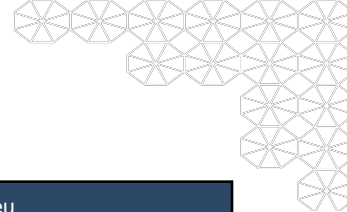


Model Experiments



- Models (same hyperparameters across models):
 - Pegasus (Baseline)
 - T5
 - BART
 - GPT/OPT350M
- Transfer learning on cleansed datasets
 - Fine-tuning with GPT/OPT350M models highlight complexity of the task
- T5 model hyperparameters fine-tuned further

Automatic Evaluation



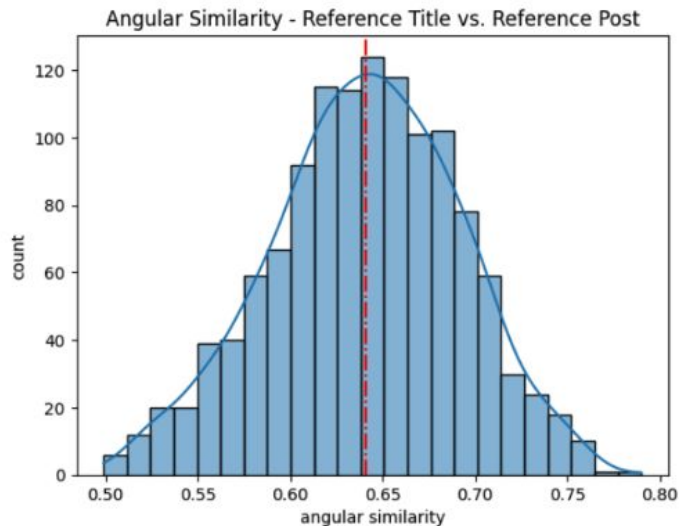
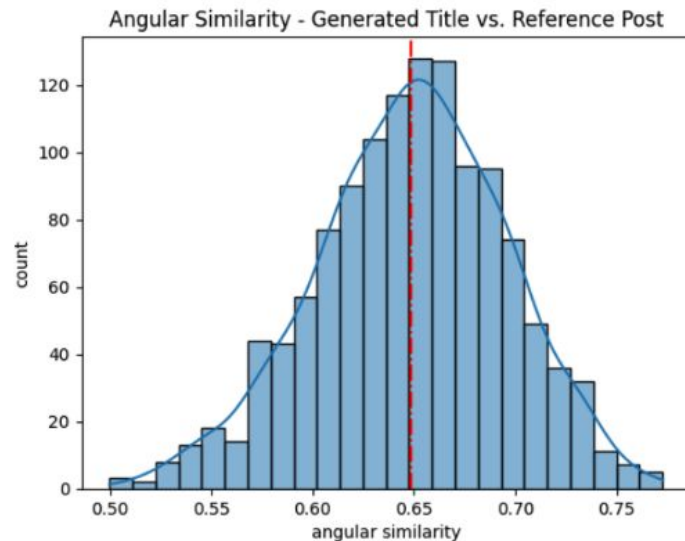
| Cand_Title-Ref-Title (N=1250) | rouge1 | rouge2 | rougeL | rougeLsum | bleu |
|----------------------------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| PEGASUS-Xsum | 0.157997 | 0.043143 | 0.14421 | 0.143903 | 0.019779 |
| T5 | 0.184472 | 0.051011 | 0.165052 | 0.165165 | 0.029681 |
| GPT-2 | 0.069966 | 0.023475 | 0.053999 | 0.053998 | 0.007463 |

| Cand_Title-Ref-Title (N=100) | rouge1 | rouge2 | rougeL | rougeLsum | bleu |
|---------------------------------|----------|---------|----------|-----------|----------|
| T5 (max_length = 64) | 0.239797 | 0.08335 | 0.219164 | 0.220178 | 0.059214 |

| | AES | | FD | |
|--------------|--------------------------------|--------------------------|-----------------------------|-----------------------|
| | Candidate Title vs Ref Post | Ref Title vs Ref Post | Candidate Title vs Ref Post | Ref Title vs Ref Post |
| PEGASUS-Xsum | 0.63724 | 0.64045 | 1.07554 | 1.06696 |
| T5 | 0.64847 | 0.64045 | 1.04622 | 1.06696 |
| GPT-2 | - | 0.64045 | 0.01173 | 1.06696 |

Automatic Evaluation

T5 Average Angular Similarity



Human Evaluation

| | Reference Title | Candidate Title V1 | Candidate Title V2 (Fine Tuned) | Candidate - Faithfulness | Candidate - Fluency | Candidate - Coherence |
|---|--|---|---|--------------------------|---------------------|-----------------------|
| 1 | is a pricey masters degree worth it | what is the best way to get a job in data science | what is the best way to get a masters in ds | 😞 | 😄 | 😞 |
| 2 | how should I start | how do i become a data analyst | Data analyst job or not | 😄 | 😄 | 😄 |
| 3 | ds masters subsequent phd studies | MS in data science vs python | Should I do a phd in data science | 😞 | 😄 | 😞 |
| 4 | crime scene dataset photo and video database | looking for datasets of crime scene images | looking for crime scene datasets | 😄 | 😄 | 😄 |

* **bolded** text indicates the best title based on the content in the original post

Conclusion

- T5 model produce the best ROUGE, BLEU, AES, and FD scores
 - Larger model
 - More adaptable to diverse tasks
- Further human evaluation needed to complement evaluations for meaningful conclusions
- Challenges from computing resources constraints