

JACOB FRIEDMAN

ITCS 5154 SPRING 2025

LINK TO PRESENTATION: PRESENTATION ON GITHUB

PROBLEM & CHALLENGES

Problem:

- **Disinformation:** Fact-checking is undeniable in contemporary politics with disinformation abound.
- **Urgency**: Need for rapid, effective verification highlighted (e.g., Trump admin's unsubstantiated claims).
- **Resources**: Issue requires significant resources (news orgs: extensive man-hours/teams for scrutiny).
- Question (Gencheva et al., 2017): Can NLP determine fact-worthiness using speech, semantic context, and surrounding text?
- Project Goal: Identify claims needing fact-checking via text and semantic analysis.

Challenges:

- Extensive hyperparameter tuning required.
- Limited computational resources (local machine & Google Colab).
- Integrating complex preprocessed data from original authors with new architecture.
- Addressing inherent data imbalance.

MY MOTIVATION

Core Motivation: Driven by palpable political uncertainty and the pervasive influx of misinformation/fabricated narratives by politicians.

The Need: Critical demand for accessible, efficient ways to identify claims needing fact-checking amidst overwhelming volume.

Interdisciplinary Approach: A multi-disciplinary perspective, combining my Political Science background with NLP techniques.



EXISTING RELATED APPROACHES

- Gencheva et al. (2017): Context-Aware Claim Detection
 - Used State Vector Machine (SVM) and Feed-Forward Networks (FNN) on annotated political debate data
 - Created dataset CW-USPD-2016 "Check-Worthiness in the US Presidential Debates 2016"
 - Leveraged rich context (debate, speaker interactions, reactions).
 - Demonstrated superior performance to baseline, highlighting context importance.
 - Limitations: Data dependency, complex feature engineering, potential annotation bias.
- Other Approaches (Indirectly Relevant):
 - Chen et al. (2021) (Social Bots):
 - Used neutral "drifter" bots on Twitter to study political bias, concluding bias stemmed from user interactions/platform mechanisms, not the algorithm itself.
 - Ash et al. (2024) (Narrative Analysis):
 - Introduced RELATIO (using SRL + entity clustering) to quantify narrative structures; applied it to the U.S. Congressional Record to analyze dynamics, sentiment, & polarization over time.



MY METHOD

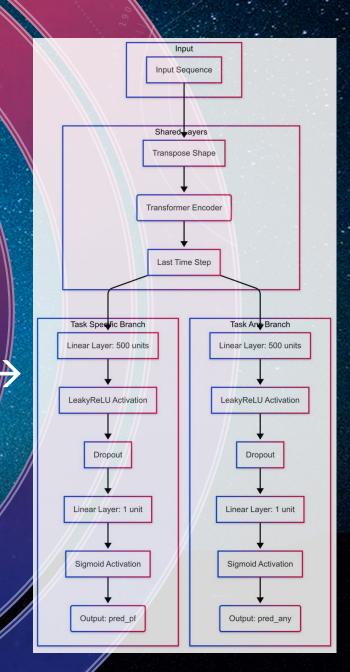
- Goal: Reimplement Gencheva et al. (2017) using Recurrent Nueral Network (RNN) & Transformer (vs. original SVM/FNN design).
- Dataset: CW-USPD-2016:
 - 4 2016 US election debates (3 presidential, 1 VP)
 - 5,415 sentences annotated by 9 fact-checkers (e.g., CNN, PolitiFact).
 - Low inter-source agreement highlights ranking task focus.
- Comparability: Used same dataset & replicated original preprocessing for fair comparison.
- Key Change: Replaced the initial SVM layer with:
 - LSTM layer (RNN model: MultiTaskRNN).
 - Transformer encoder layer (Transformer model: MultiTaskTransformer).
- Architecture: Maintained original subsequent layers (Linear, Leaky ReLU, Sigmoid) & task branching.

Input Sequence Shared ayers Bi-directional LSTM Last Time Step Output Task Any Branch Task Specific Branch Linear Laver: 500 units Linear Layer: 500 units LeakyReLU Activation LeakyReLU Activation Dropout Dropout Linear Layer: 1 unit Linear Layer: 1 unit Sigmoid Activation Sigmoid Activation Output: pred_pf Output: pred_any

ARCHITECTURE DIAGRAMS

← MultiTaskRNN Model

MultiTaskTransformer Model **



EXPERIMENTAL STEPS



1. Data Pre-processing:

Preprocessing Pipeline: Replicated original authors' complex pipeline using their code

Data Loading: Loaded raw debate transcripts; partitioned into train/validation sets.

Feature Extraction: Converted text to numerical format (using context, POS tags, style features).

Label Extraction: Extracted checkworthiness labels from various sources (e.g., NPR, CNN, PolitiFact).



2. Model Implementation:

Implemented two architectures based on Gencheva et al (2017):

- MultiTaskRNN: Shared LSTM layer for temporal dependencies, followed by task-specific branches (Linear, Leaky ReLU, Dropout, Sigmoid).
 - MultiTaskTransformer: Shared Transformer Encoder using selfattention, followed by similar task-specific branches.



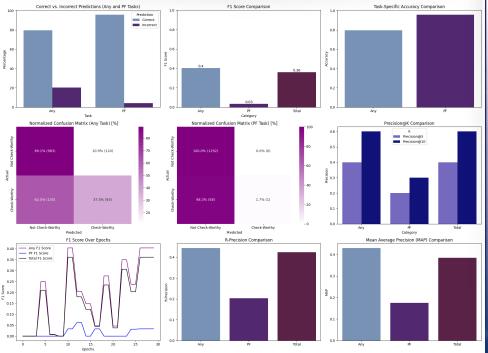
3. Model Training & Evaluation:

Hyperparameter Tuning: Systematic Bayesian Optimization (w/k-fold CV & early stopping).

Tuning Phases (Iterative): Broad search - > Optimizer focus -> Architecture focus

Training: Used optimal hyperparameters & Binary Cross-Entropy loss (with multitask variations).

Evaluation: Assessed final models on held-out validation set (analyzing metrics & visualizations).



RESULTS & OBSERVATIONS

Best Performing Model:

- Un-Weighted MultiTaskTransformer w/ Combined Score validation.
- Highest F1 scores for "Any" (~0.40) & "Total" (~0.36) tasks -> better precision/recall.
- Improved "Check-Worthy" identification for "Any" task (37.5% correct).
- Enhanced Precision @ K (more relevant claims in top predictions).

General Observations:

- Accuracy often misleading due to class imbalance; F1 score more reliable.
- All models struggled significantly with the "PF" (PolitiFact) task.
- Combined score validation generally boosted F1 performance over average loss (esp. for Transformer).
- Task weighting showed inconsistent benefits; unweighted was best for top Transformer model.
- Ranking performance (MAP scores) didn't improve as much as F1 scores.

CONCLUSION & FUTURE WORK

Conclusion:

- Best model (Un-Weighted Transformer w/ Combined Score) is promising, but challenges persist.
- Improved precision/recall achieved for general ("Any") claim detection.
- Needs Improvement: Performance on "PF" task and overall claim ranking.

Future Work:

- Explore advanced evaluation metrics (beyond average loss).
- Investigate dynamic/adaptive task weighting.
- Apply specialized loss functions (e.g., focal loss) for class imbalance (esp. "PF" task).
- Explore RNN/Transformer architecture variations (e.g., hybrids) & further optimization.



Works Cited:

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 Neutral Bots Probe Political Bias on Social Media. Nature Communications, 12, 5580.
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- Gencheva, P., Koychev, I., Màrquez, L., Barrón-Cedeño, A., & Nakov, P. (2017). A Context-Aware Approach for Detecting Check-Worthy Claims in Political Debates. Proceedings of Recent Advances in Natural Language Processing (pp. 267–276). Varna: INCOMA Ltd. doi:https://doi.org/10.26615/978-954-452-049-6_037

THANK YOU!

For more details and the full experimental accounting:

Check out my GitHub here: TECS5154CourseProject on GitHub

Check out my full report here:

PDF of Full Report on GitHub

Check out my presentation here:

Presentation Video on GitHub