Automated Misinformation Detection with Natural Language Processing and Network Science Models

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Thesis Proposal

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Agenda

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Key Definitions

- Claim = an assertion of the verifiable truth of something.
  - Examples of claims:
    - Masks don’t prevent COVID-19 infections.
    - Russia invaded Ukraine to protect ethnic Russians.
  - Examples of statements that are not claims:
    - Nobody should be forced to wear a mask.
    - Russia’s invasion of Ukraine is sad.
- Misinformation = false information spread, **regardless of the intent to mislead**
- Disinformation = false information deliberately spread to deceive people
  - A subset of misinformation with a known motive
- Propaganda = information, ideas, or rumors deliberately spread widely to help or harm a person, group, movement, institution, nation, etc.
  - Could contain misinformation (or disinformation), but could also be completely truthful
- Conspiracy Theory = a theory that rejects the standard explanation for an event and instead credits a covert group or organization with carrying out a secret plot

What this System will Attempt to Detect

- In scope:
  - Misinformation, and therefore, disinformation – but we will not attempt to differentiate these by detecting intent to deceive.
  - The subset of propaganda that employs misinformation.
  - The (majority) subset of conspiracy theories that employ misinformation.
- Out of scope:
  - Propaganda that employs only truthful information.
  - Conspiracy theories that only rely on factual information.

Misinformation is a Profound Societal Risk

- World Economic Forum’s Global Risks Report 2024 cites misinformation as the biggest immediate risk to humanity
- Misinformation has the potential to disrupt:
  - Political polarization and elections
    - Ex) False information could be used to promote political violence against susceptible populations
  - Public health responses and policy
    - Ex) Safe vaccines could go unused, creating a resurgence of previously eradicated diseases
  - Freedom of speech and the press
    - Ex) Countries could be empowered to take a heavy-handed approach to censorship under the guise of protecting the public from misinformation

Researching Misinformation is Critical to Mitigating these Risks

- Even with the most aggressive censorship practices, it is impractical to irradicate misinformation and its effects completely

- Given its ever-presence, understanding how misinformation emerges (and, in some cases, how it is purposefully employed) can inform:
  - “Inoculation” strategies that educate the public how to identify misinformation
  - Countermeasures that directly counter misinformation
  - A better understanding of the societal and information space conditions that lead to misinformation propagation

Current Methods for Misinformation Detection are Inadequate to Support Research

- Existing fact-checkers determine the truth value of a message using one of:
  - Manual adjudication of claims
  - Semi-automated techniques that detect claims that are “check-worthy” and send them to human adjudicators
  - Fully-automated techniques that check “check worthy” claims against repositories of facts
- An ideal misinformation detection system would be:
  - Fully automated
  - Unbiased by human fact-checkers or information repositories
  - Able to leverage both the content and the social context of a piece of information

Thesis Research Questions

- **Q1: How can we detect misinformation in large datasets at the post level in a way that is useful for social cybersecurity research?**
- **Q2: How is misinformation used in information operations?**
  - **Q2.1: Does the base rate of misinformation use differ between the BEND maneuvers?**
  - **Q2.2: Do different actors employ misinformation differently in their maneuver sets?**
  - **Q2.3: Is misinformation linked to more effective maneuvers?**

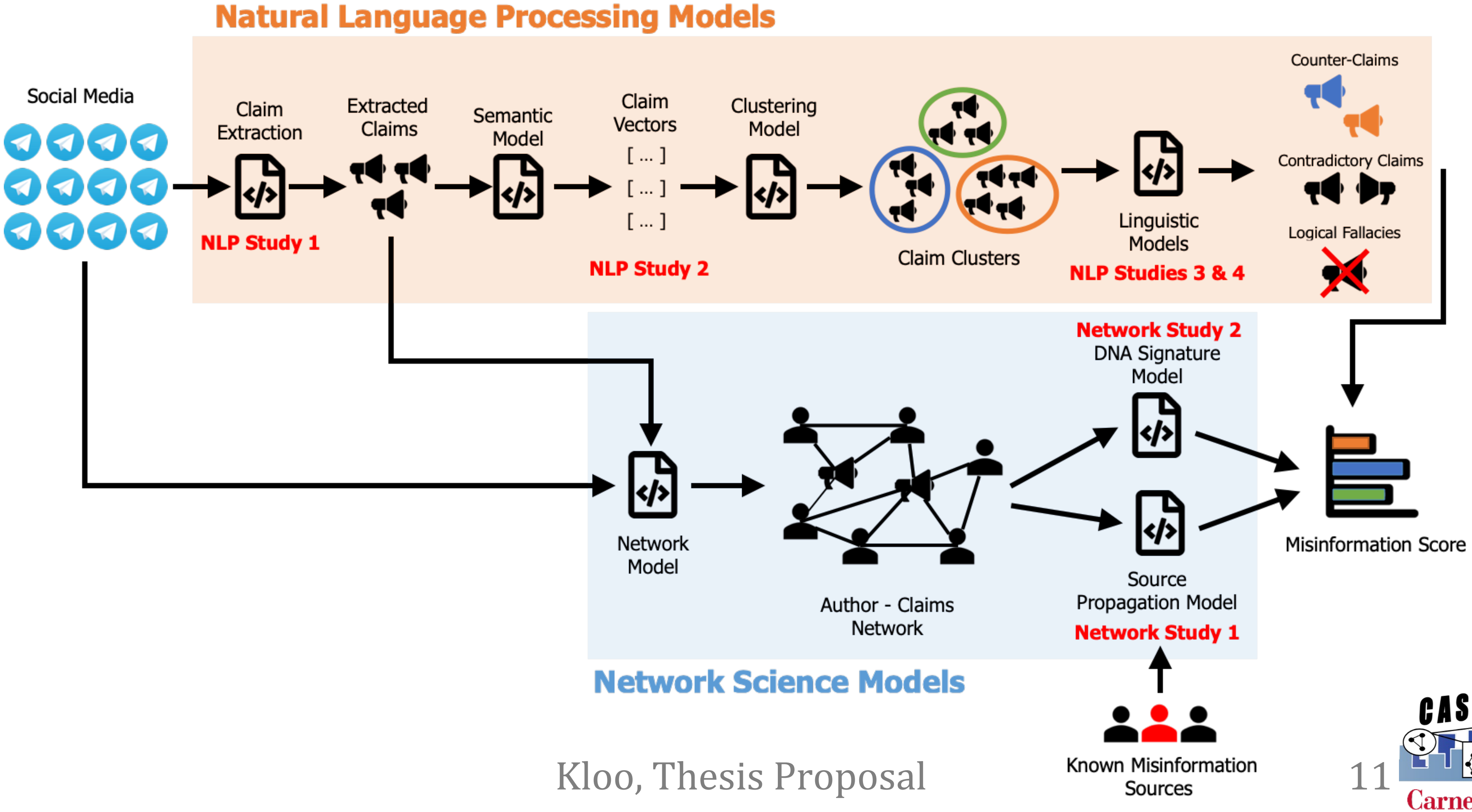
How this fits within the existing social cybersecurity research context

- BEND provides a framework for describing information space maneuvers according to their intents (and, soon, their effects)
- Key components of BEND analyses:
  - Content:
    - Topics (***what*** are they discussing?)
    - Stance (***what side*** of the issue?)
    - Linguistics (***how*** are they talking about it?)
  - Tactics:
    - Bots (***how*** are they employed?)
    - **Misinformation** (***how*** is it incorporated in maneuvers?)

Key Theory – Claims Indicate Potential Misinformation

- Misinformation is shared using claims
- Some claims **negate** each other, so there are two possibilities:
  - Both claims are false
  - One claim is true and the other is false
  - Both claims cannot be true, so at least one is misinformation
- Logical fallacy detection and network approaches indicate which claim(s) is/are likely misinformation

Misinformation Detection Pipeline



Detection Pipeline Requirements

Scalable/fast enough to run on a laptop (with reasonable data size)

Integrates with ORA, Netmapper, and Botbuster

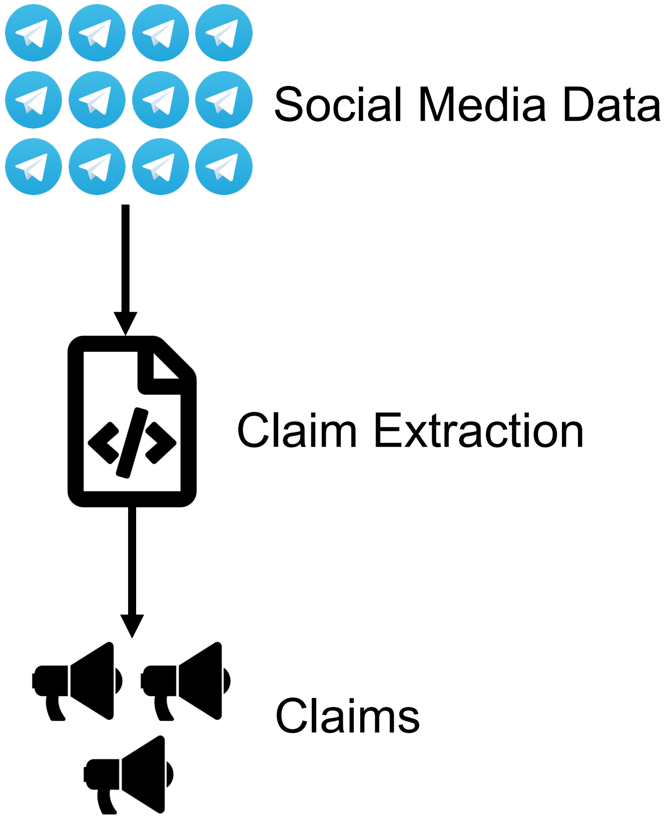
Either work seamlessly along these tools or be integrated directly into one of them (e.g., as an ORA report)

Agnostic to specific social media platforms

Can leverage, but not rely on features specific to one platform (e.g., hashtags, retweets)

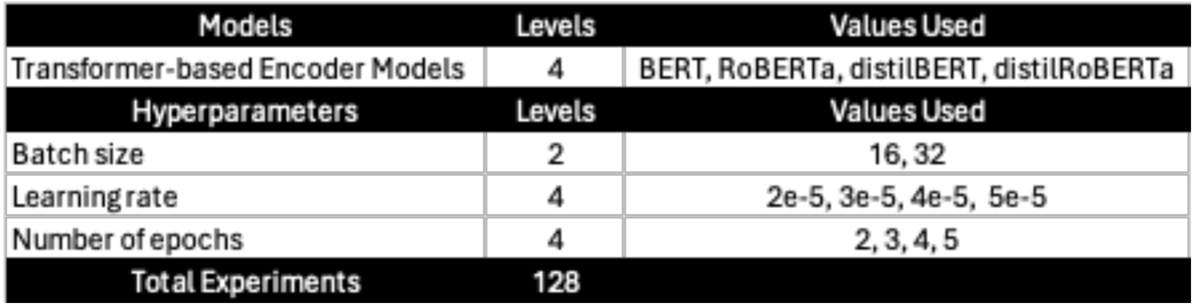
NLP 1: Claim Extraction (Overview)

- Goal = unsupervised identification and extraction of claims from social media text
- Method overview:
  - A two-layer modeling approach:
    1. Classify social media messages as containing or not containing a claim.
    2. Extract the claim span from the message.
- Notable existing work:
  - Rarely applied to social media
  - SemEval-2023 task focused on Twitter, but only on **causal** claims related to **medicine**
  - CheckThat! 2019 and 2021 tasks focused on the **check-worthiness** of **COVID-19 and political** claims on Twitter, but this disregards claims that cannot be fact checked and those in other domains
- Contribution = expand claim detection to generalize across topics and on multiple social media platforms (not just Twitter).



NLP 1: Claim Extraction (Message Classification)

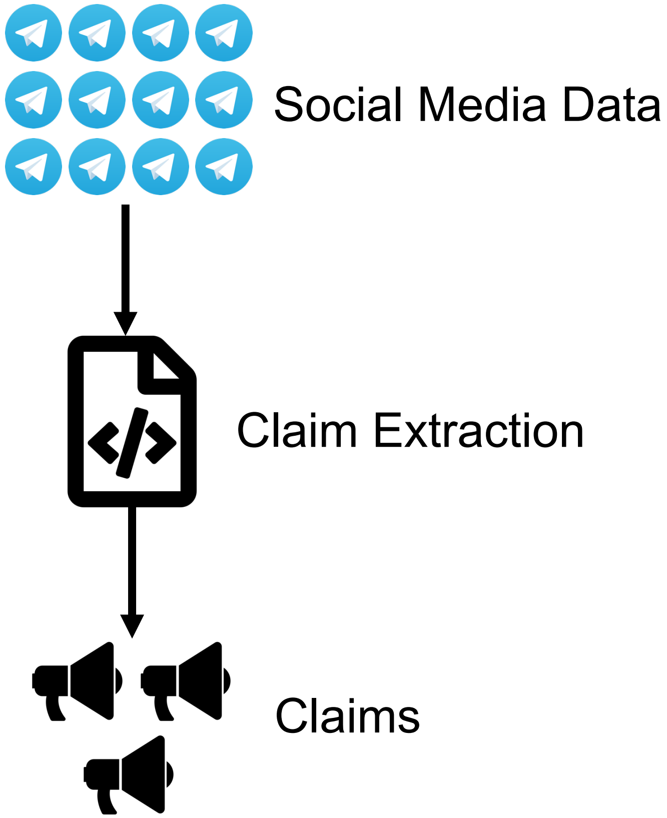
- Input = social media text
- Output = binary label (contains claim or not)
- Training Data:
  - Text → binary label (contains claim or not)
- Modeling:
  - Stage 1: **task-tune** several transformer models (distilBERT, BERT, RoBERTa, distilRoBERTa) to classify messages that contain claims, select best model.
  - Stage 2: domain-adaptive pre-training (**DAPT**) on social media data to improve classification performance.
  - Stage 3: ensemble multiple models to create **voting classifier**, evaluate computation cost/benefit for any performance increase



Models	Levels	Values Used
Transformer-based Encoder Models	4	BERT, RoBERTa, distilBERT, distilRoBERTa
Hyperparameters	**Levels**	**Values Used**
Batch size	2	16, 32
Learning rate	4	2e-5, 3e-5, 4e-5, 5e-5
Number of epochs	4	2, 3, 4, 5
Total Experiments	**128**	

NLP 1: Claim Extraction (Sequence Tagging)

- Input = social media text containing a claim
- Output = span of text (sequence) with only the claim
- Training Data:
  - Text with known claim → labeled text span with only the claim
- Modeling:
  - Stage 1: **task-tune** several **transformer** models (distilBERT, BERT, RoBERTa, distilROBERTa) to extract claim spans using **token labeling**. If message classification study shows DAPT improvements, can re-use those DAPT models here.
  - Stage 2: **task tune** encoder-decoder model (T5) to test against the transformer baseline.
  - Stage 3: **prompt-engineer** for few- and zero-shot learning with generative LLMs to test performance.
  - Stage 4: evaluate potential **ensemble approach**, with the understanding this will likely be computationally infeasible (and tends not to work as well with span extraction)



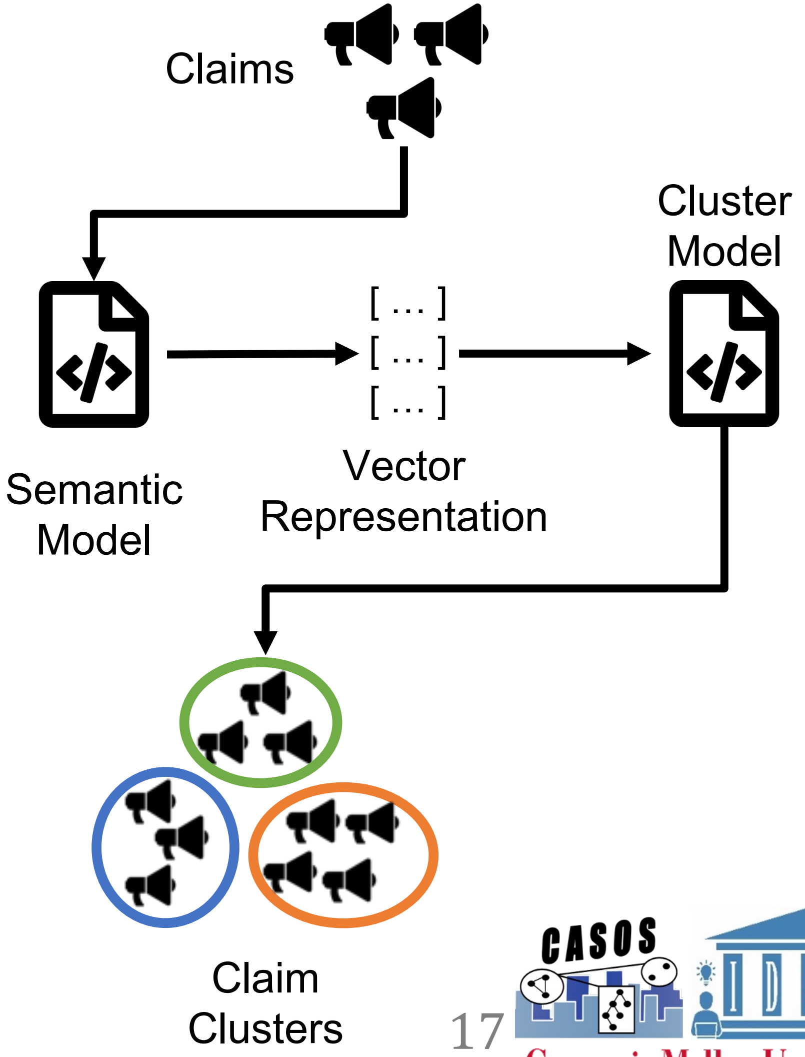
Social Media Data

Claim Extraction

Claims

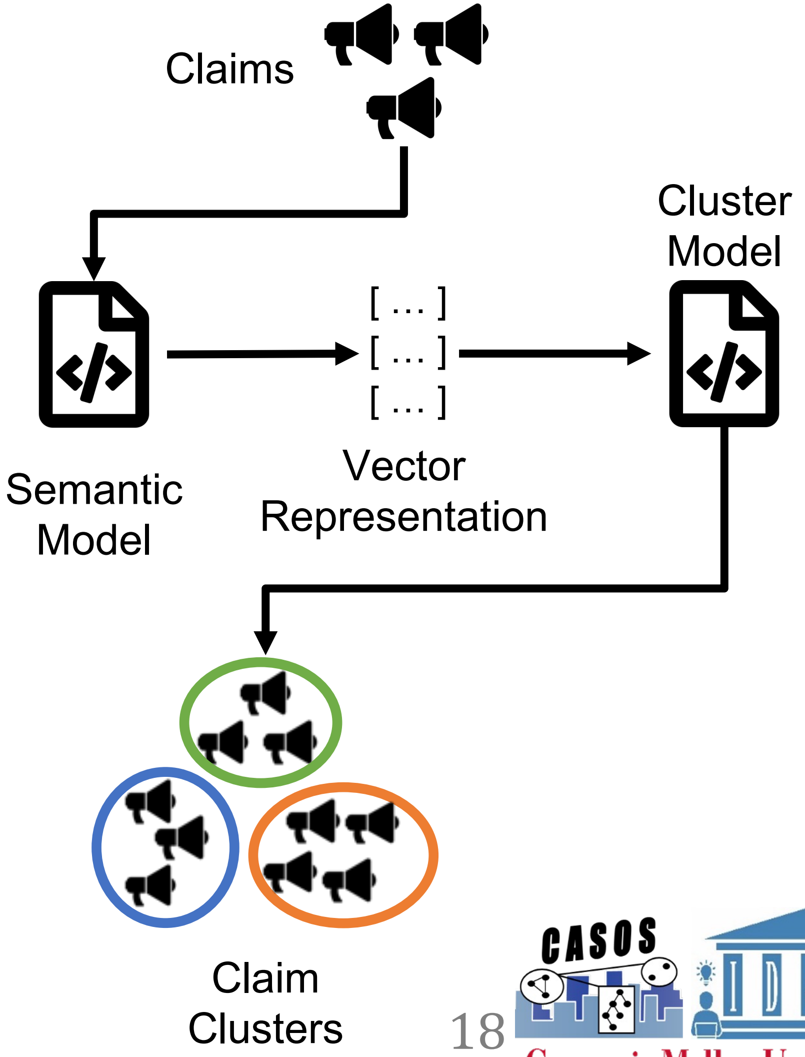
NLP 2: Claim Clustering (Overview)

- Goal = group claims that are about similar topics
- Method overview:
  - R1: Directly cluster claims by converting into vector space using semantic similarity and clustering.
  - R2: Extract entities from claims, create a bipartite graph of claims to entities, and cluster.
- Notable existing work:
  - BERTopic – generalized topic detection using semantic embeddings
  - SciClops – clustering scientific claims using hybrid embedding/network methodology
- Contribution = unsupervised claim clustering that generalizes across topics.



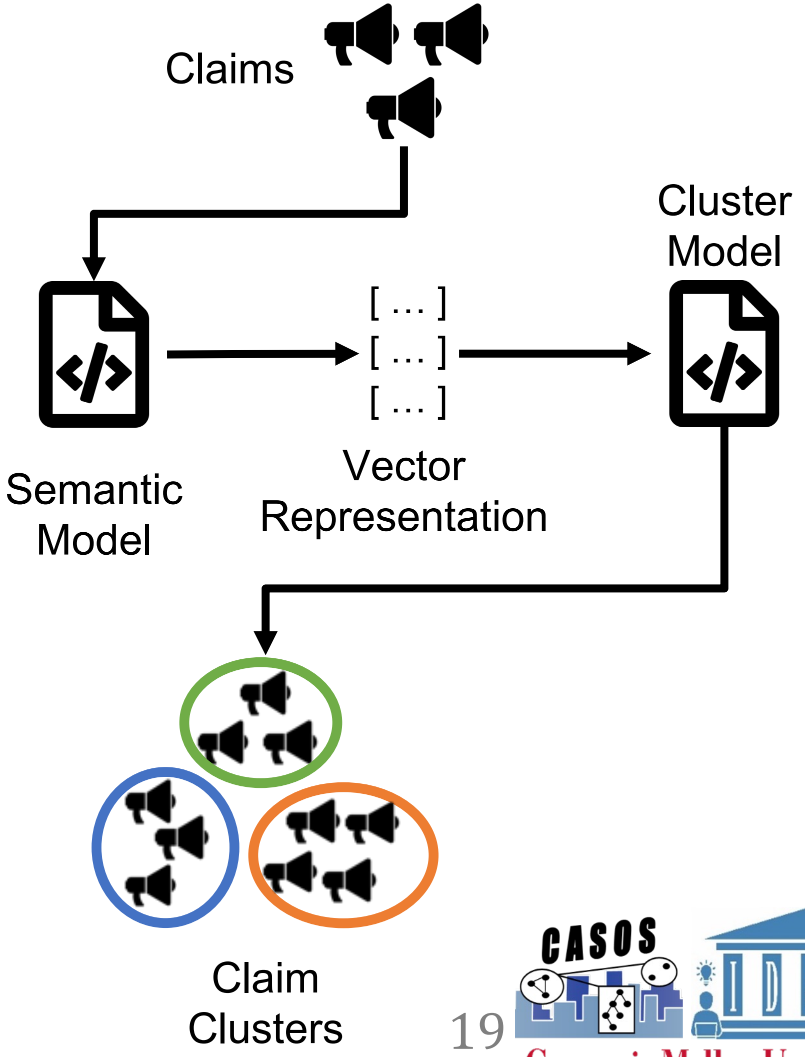
NLP 2: Claim Clustering (Semantic Clustering)

- Input = set of claims
- Output = clustered groups of claims based on topic
- Modeling:
  - Stage 1: represent claims as vectors (experiment with different embedding models)
  - Stage 2: reduce dimensionality with UMAP or PCA (test to see which is more performant)
  - Stage 3: cluster vectors using k-means (tuning k with the elbow method) or HDBSCAN, depending on the data size



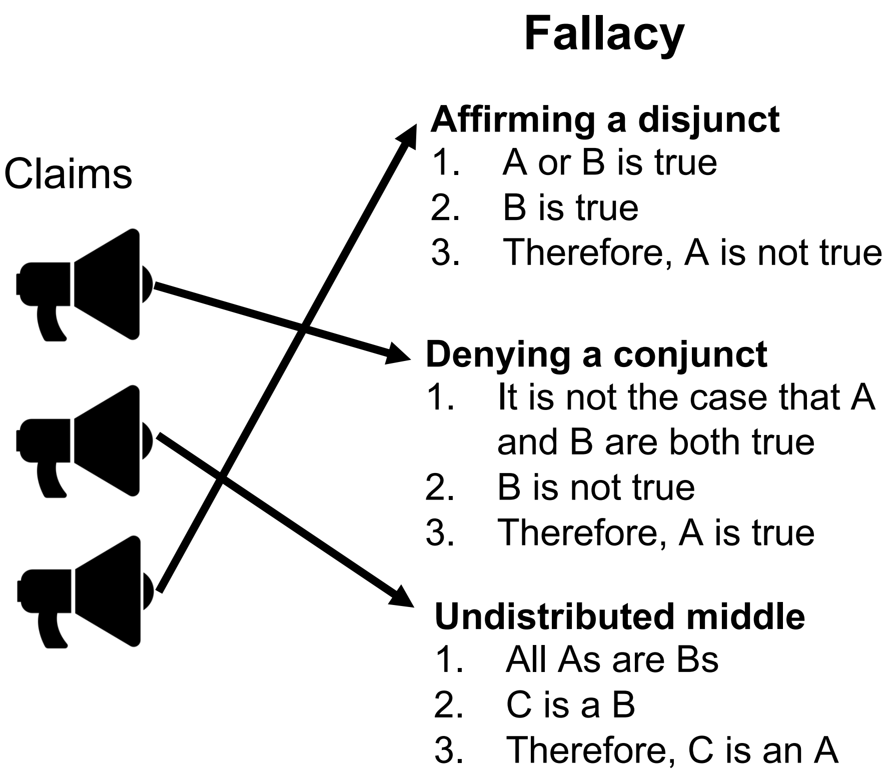
NLP 2: Claim Clustering (Entity Graph)

- Input = set of claims
- Output = clustered groups of claims based on similar entities
- Modeling:
  - Stage 1: extract entities from claims using named entity extraction (NER)
  - Stage 2: create a weighted bipartite graph of entities to claims
  - Stage 3: cluster the claims (evaluate existing community detection algorithms that operate on bipartite graphs)



NLP 3: Logical Fallacies (Overview)

- Goal = detect the presence of logical fallacies in a claim
- Data = raw social media text containing a claim, labeled as containing a fallacy or not (result of claim classification study).
- Method Overview:
  - Binary classification of claims (contains fallacy or does not) using encoder models (BERT), encoder-decoder models (T5), and generative models (GPT).
  - Fine-tune on social media and determine which is the best cost/performance tradeoff
- Notable Existing Work:
  - Study demonstrated performance of different transformer models, but many new NLP techniques have emerged since this work.
- Contribution = Reframes fallacy detection from a multi-classification problem (identifying a specific fallacy) to a binary classification model that finds claims containing any fallacy. Also, generalizes across topics.



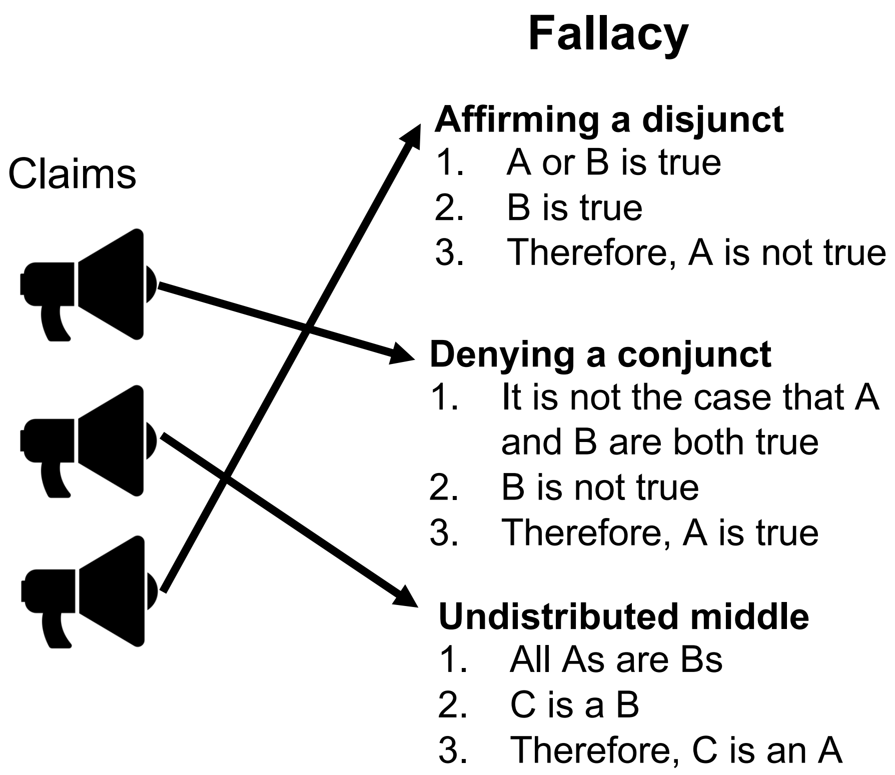
Affirming a disjunct
1. A or B is true
2. B is true
3. Therefore, A is not true

Denying a conjunct
1. It is not the case that A and B are both true
2. B is not true
3. Therefore, A is true

Undistributed middle
1. All As are Bs
2. C is a B
3. Therefore, C is an A

NLP 3: Logical Fallacies (Classification/Detection)

- Input = social media claims, some contain logical fallacies
- Output = binary label (contains fallacy or not)
- Modeling:
  - Stage 1: domain adaptive pre-training (DAPT) transformer models (distilBERT, distilRoBERTa, BERT, RoBERTa) on large repositories of claims (adapting from models tuned on regular text).
  - Stage 2: task-tune models for binary classification of text containing logical fallacies.
  - Stage 3: task/domain-tune encoder-decoder model (T5) for binary classification of logical fallacy.
  - Stage 4: few and zero-shot prompt engineering for generative LLMs.
  - Stage 5: evaluate each method in terms of computational cost/performance.



Fallacy

Affirming a disjunct

1. A or B is true
2. B is true
3. Therefore, A is not true

Denying a conjunct

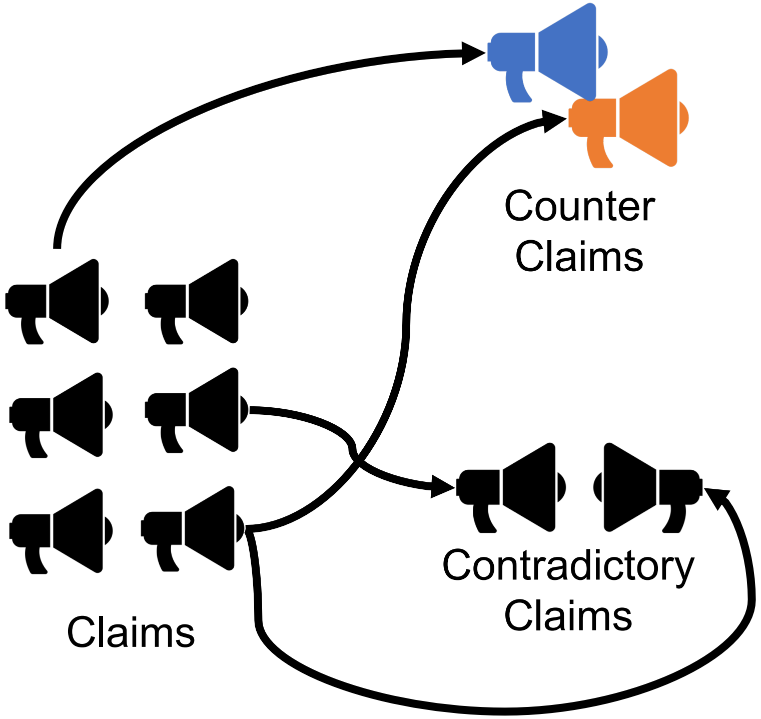
1. It is not the case that A and B are both true
2. B is not true
3. Therefore, A is true

Undistributed middle

1. All As are Bs
2. C is a B
3. Therefore, C is an A

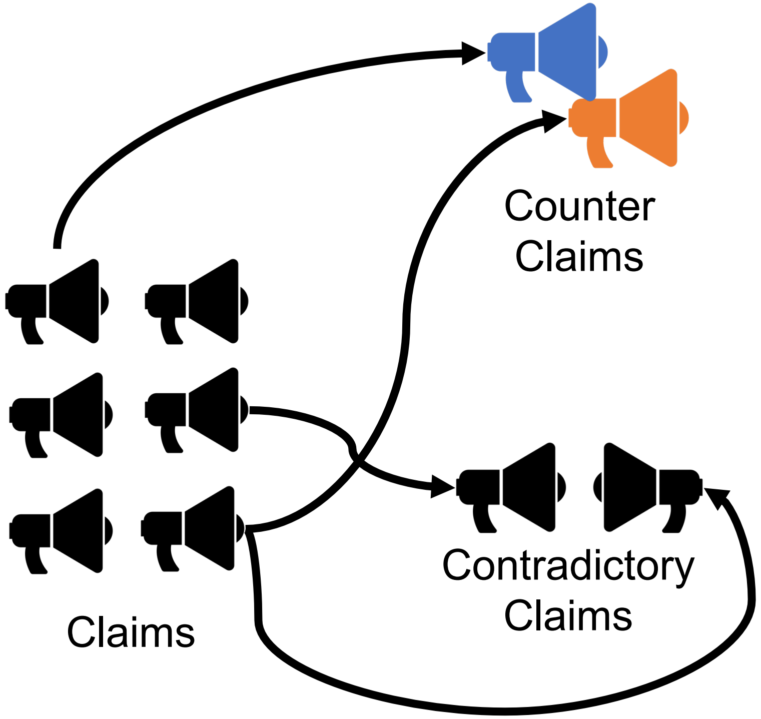
NLP 4: Counter and Contradictory Claims (Overview)

- Goal = detect counter and contradictory claims
- Data = pairs of claims tagged as counter, contradictory, or neither.
- Method Overview:
  - R1: build semantic networks of claims, use network features to detect opposing claims.
  - R2: train encoder model (BERT) and/or encoder-decoder model (T5) to classify pairs of claims as contradictory.
- Notable Existing Work:
  - Several studies demonstrate that BERT models are more effective than older neural network-based techniques for finding contradictory claim pairs, but their methods are out-of-date.
  - Study demonstrates how semantic networks can be used to detect contradictions, but their model is bogged down by also attempting to extract claims from text.
- Contribution:
  - A 2-pass approach using semantic networks and fine-tuned transformer models to identify pairs of counter and contradictory claims.



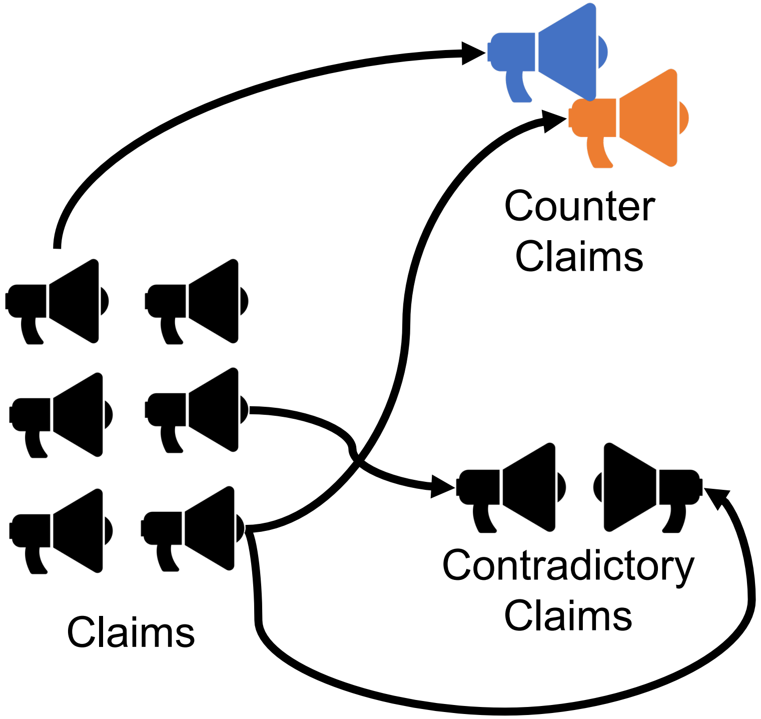
NLP 4: Counter and Contradictory Claims (Semantic Networks)

- Input = pairs of claims, extracted from social media text
- Output = labeled pairs of claims denoting if they are counter-claims, contradictory, or neither
- Modeling:
  - Stage 1: create semantic network from claims (using Netmapper)
  - Stage 2: manually identify subgraphs that correspond to counter and contradictory claims
  - Stage 3: identify unique network features between these subgraph pairs.
  - Stage 4: algorithm to search for subgraph pairs.



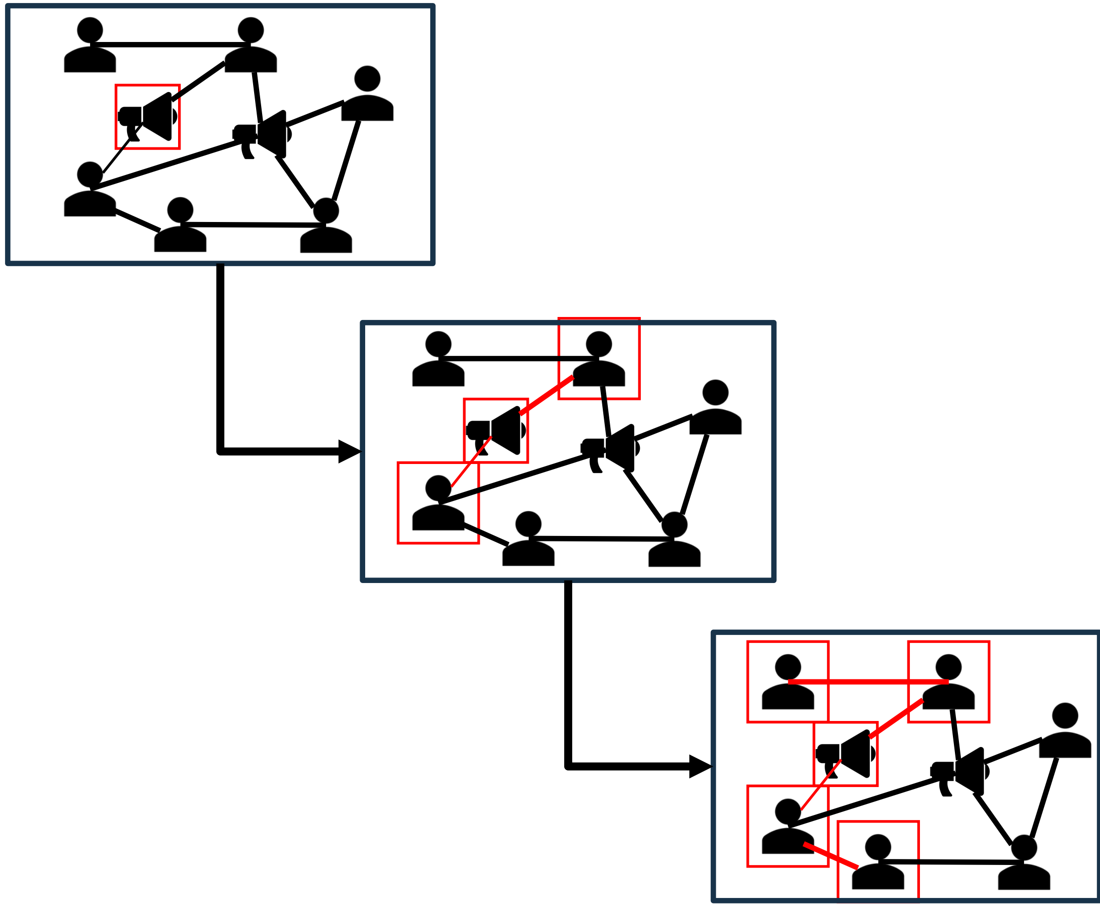
NLP 4: Counter and Contradictory Claims (Multi-Classification of Claim Pairs)

- Input = pairs of claims, extracted from social media text
- Output = labeled pairs of claims denoting if they are counter-claims, contradictory, or neither
- Modeling:
  - Stage 1: use repository of claims (preferably data from outside of the training data) to perform DAPT on transformer models to prepare them for use with claims.
  - Stage 2: task-tune the DAPT models for the multi-classification tasks of identifying counter and contradictory claims (or neither).
  - Stage 3: evaluate against zero- and few-shot training of encoder-decoder models (T5)
  - Stage 4: evaluate against reframing as two separate binary classification problems (counter or zero label; contradictory or zero label)



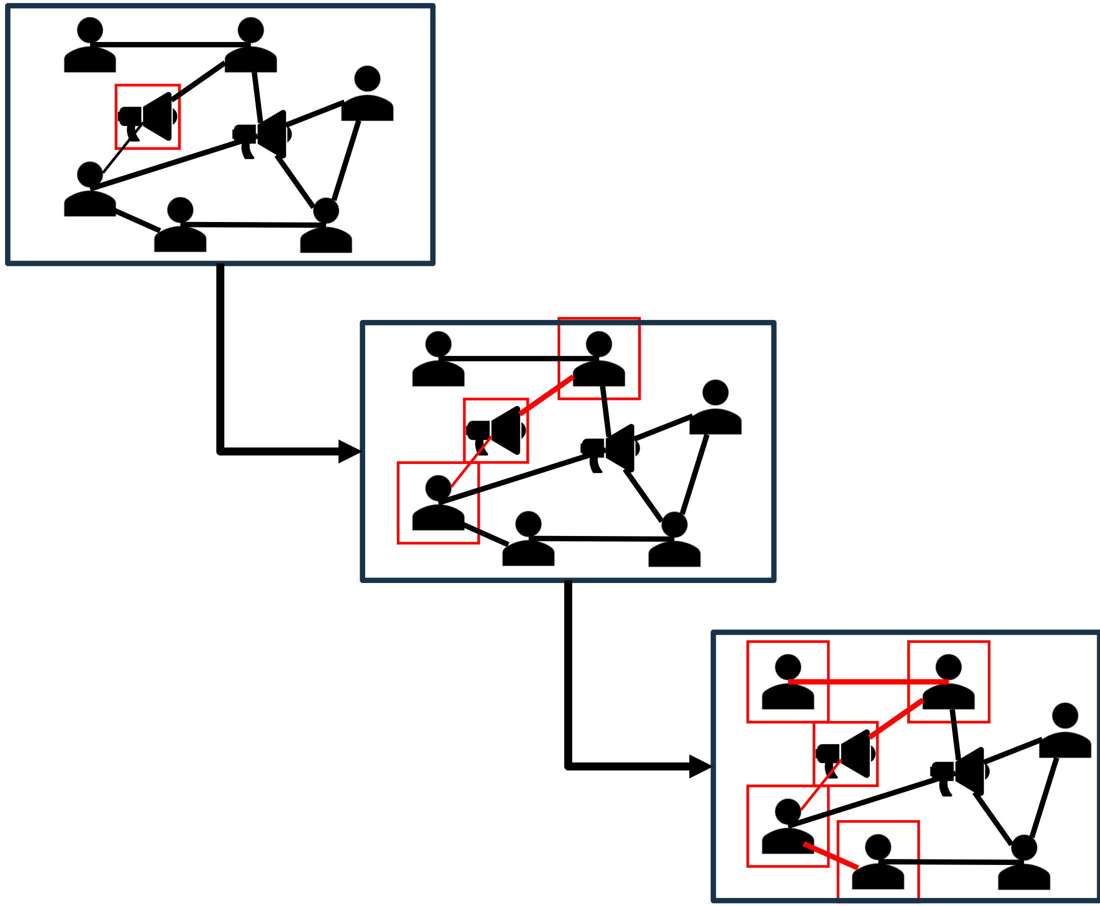
Network 1: Unreliable Source Propagation (Overview)

- Goal = locate users likely to post unreliable information and propagate reliability through social networks.
- Data = Twitter, Reddit, and Telegram data on COVID-19, US Politics, and Russia/Ukraine
- Method Overview:
  - Extract and label URLs in social media according to their reliability (using things like Media Bias Ratings)
  - Infer user reliability based on their relationships to URLs, and propagate to other users using social ties.
- Notable Existing Work:
  - Study demonstrates a methodology to propagate stance through social media using network features.
  - Several studies demonstrate demonstrate a methodology for trust propagation through social networks.
- Contribution:
  - An automated methodology for inferring the reliability of users in social graphs built from varied social media sources.



Network 1: Unreliable Source Propagation (Detection and Propagation)

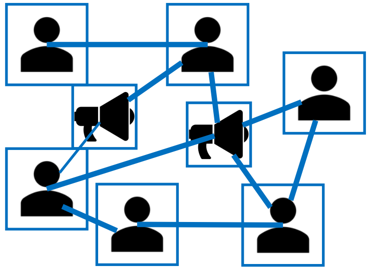
- Inputs = social media data containing at least network information and URLs
- Outputs = user labels for inferred reliability
- Modeling:
  - Stage 1: parse social media into network structure, extracting URLs (done with ORA)
  - Stage 2: crash URLs into repositories of media reliability (e.g., Media Bias Ratings) to generate a reliability score. Seek to use multiple repositories to limit potential bias.
  - Stage 3: propagate reliability from URLs to users using methods similar to the existing stance and trust propagation methodologies.
  - Stage 4: tune the propagation methods to leverage features from specific social media platforms (e.g., ”retweets” are specific to Twitter, so creating a Twitter-specific sub-model that improves performance over the base model).
- Validation:
  - Group authors into 3 bins: reliable, unknown reliability, and unreliable
  - Using data labeled with known misinformation (see slide 34), determine the average proportion of misinformation shared for the authors in each reliability bin
  - Use a permutation test to determine if the authors labeled as less reliable propagate misinformation at a statistically significantly higher rate compared to those with lower reliability scores



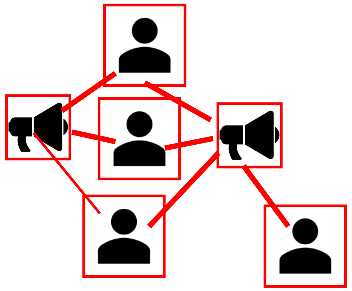
Network 2: Dynamic Network Signature of Misinformation Campaigns (Overview)

- Goal = identify social network features that are indicators of misinformation propagation.
- Data = Twitter, Reddit, and Telegram data on COVID-19, US Politics, and Russia/Ukraine
- Method Overview:
    - Find and label subgraphs where known misinformation is being shared and another set of subgraphs where it is verified that misinformation is not being shared.
    - Compare (using dynamic network analysis) subgraphs with positive and negative labels to find generalizable differences between misinformation networks and those that do not share misinformation.
- Notable Existing Work:
    - Study identified network signatures of misinformation on Twitter during the 2016 US presidential election.
    - Many studies describe network characteristics of communities sharing misinformation, but few compare to similar communities sharing legitimate information.
- Contribution:
    - Generalizable network signatures of misinformation-propagating networks that can be used to identify potential misinformation.

Network without Misinformation



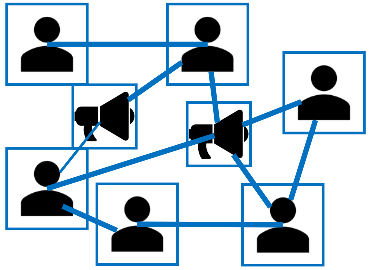
Known Misinformation Network



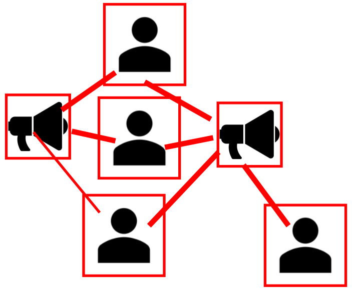
Network 2: Dynamic Network Signature of Misinformation Campaigns (DNA Analysis)

- Inputs = social media data containing at least network information
- Outputs = subgraph labels that indicate the likelihood that misinformation is present
- Modeling:
    - Using datasets with labeled misinformation (described on slide 34), identify subnetworks that support the spread of misinformation and those that do not
    - Using ORA, extract dynamic network statistics from each subnetwork, creating a dataset where a row is a subnetwork with columns containing network features and a label (supports or does not support misinformation)
    - Construct (and validate) a machine learning classifier to differentiate between subnetworks that contain misinformation
    - Conduct variable importance analysis to identify network features that are most useful for differentiating the subnetworks

Network without Misinformation



Known Misinformation Network



Proposed Detection Pipeline Data

- Platforms: Twitter, Reddit, Telegram, and Facebook
- Topics: COVID-19, Russian invasion of Ukraine, US Elections
- 24,000 messages is on-par with the dataset sizes used by the CheckThat! Claim Detection Competitions
- At least 3 raters will tag each message, highlighting claims
- Rater agreement will be calculated with Fleiss' Kappa, with the goal of achieving 0.80 or higher

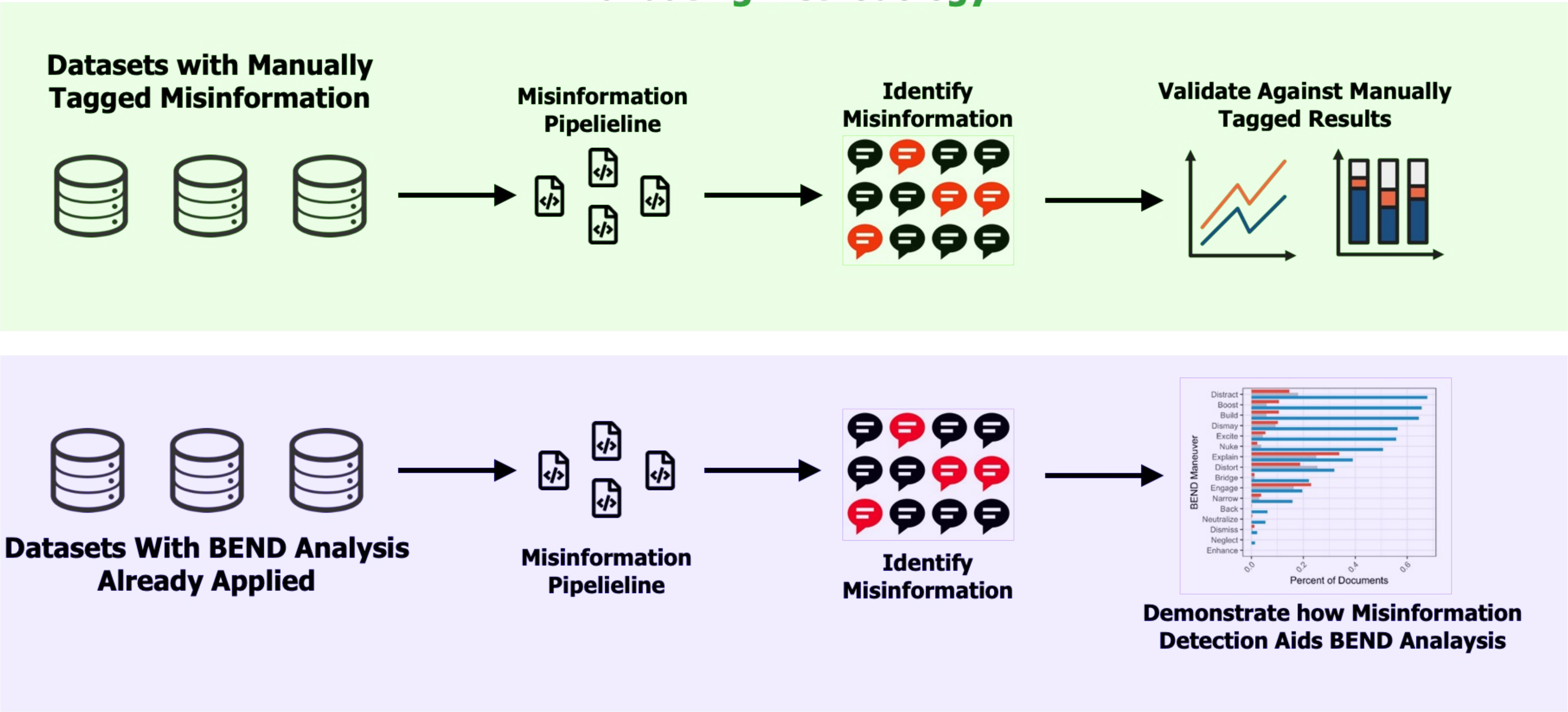
Platform	Topic	Data Size	Have Data?	Claims Tagged
Twitter	COVID-19	2,000	Yes	Yes
	US Politics	2,000	Yes	No
	Russian Invasion	2,000	Yes	No
Reddit	COVID-19	2,000	Yes	No
	US Politics	2,000	Yes	No
	Russian Invasion	2,000	Yes	No
Telegram	COVID-19	2,000	Yes	No
	US Politics	2,000	No	No
	Russian Invasion	2,000	Yes	No
Facebook	COVID-19	2,000	No	No
	US Politics	2,000	No	No
	Russian Invasion	2,000	No	No
	Total	24,000		
	Total to Label	22,000		

Proposed Detection Pipeline Data

- Logical fallacy dataset:
  - Label positively identified claims as containing logical fallacy or not (binary)
  - Goal >= 500 claims per platform (2,000 total)
- Claim pairs dataset:
  - Annotate (multi-class) as counter-claim, contradictory, or neither
  - Goal = 1,000 pairs of claims per platform (4,000 total)

Validation Pipelines

Validating Methodology



Datasets with Manually Tagged Misinformation → Misinformation Pipelieline → Identify Misinformation → Validate Against Manually Tagged Results

Datasets With BEND Analysis Already Applied → Misinformation Pipelieline → Identify Misinformation → Demonstrate how Misinformation Detection Aids BEND Analaysis

Validating Research Utility

Validation Study 1: Methodology Validation

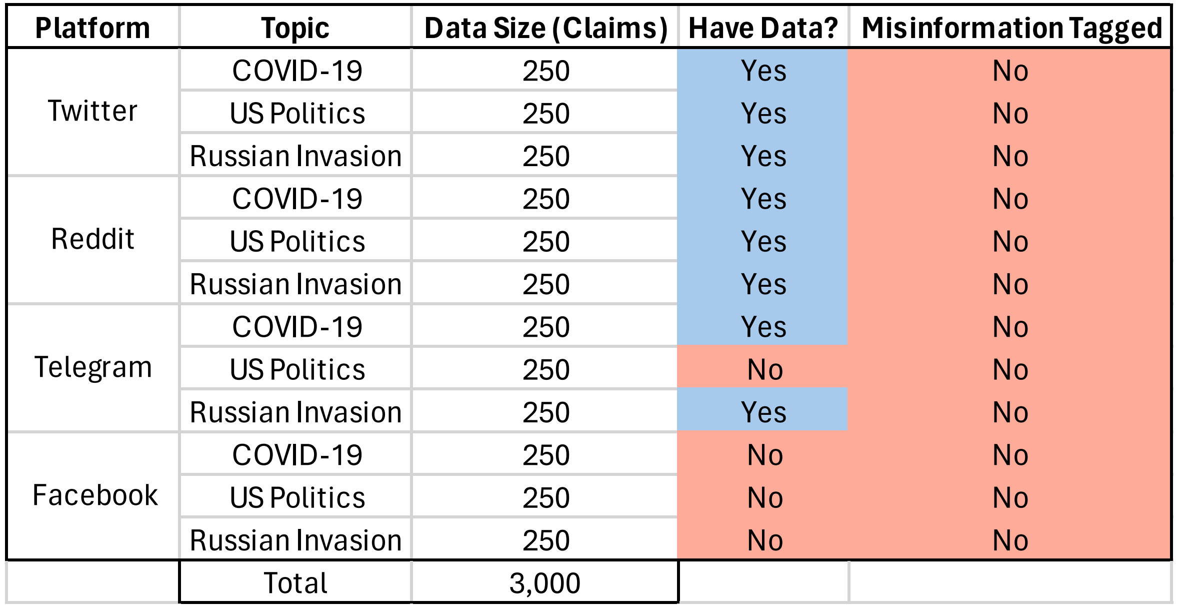
- Goal = assess the misinformation pipeline’s ability to correctly identify misinformation in social media data
- Data = Twitter, Reddit, Telegram, and Facebook data on COVID-19, US Politics, and Russia/Ukraine, tagged as misinformation/not at the post level
- Method
  - Process tagged social media data with the misinformation pipeline, assigning a score to each message
  - Determine the optimal threshold for assigning a binary “misinformation” or “not” tag by plotting a curve showing the F1 statistic using all possible thresholds, selecting the threshold that maximizes F1
  - Perform error analysis at the platform and topic levels, identifying if the methodology fails to generalize over either feature
  - Measure the contributions of each sub-model (counter/contradictory claims, logical fallacy, dynamic network analysis, and source reliability propagation) using a “leave one out” approach
    - Iteratively rerunning the misinformation pipeline without a sub-model, recomputing the optimal F1statistic
    - Determining the F1 ”loss” associated with leaving out a specific sub-model

Validation Study 2: Research Utility Validation

- Goal = assess the misinformation pipeline's usefulness in research applications
- Data = Twitter, Reddit, Telegram, and Facebook data on COVID-19, US Politics, and Russia/Ukraine, tagged as misinformation/not at the post level
- Method
  - Use ORA's BEND report to identify maneuvers in all of the datasets combined
  - Using the tagged data, determine the proportion of misinformation messages used within each BEND maneuver and form a rank-ordering
  - Repeat the rank-ordering process using the system-tagged data, forming another rank-ordering
  - Compare the human-tagged and system-tagged results using Spearman correlation to assess the similarity between the research conclusions

Proposed Validation Data

- Datasets are the same as proposed for the pipeline-development studies, but the tagging process is different (and much more labor-intensive)
- 250 claims (extracted using the methodology in the NLP 1 study) in each dataset will be tagged as containing misinformation or not using human-raters
- At least 3 human raters will be trained to use repositories such as PolitiFact, FactCheck.org, and SciCheck to manually determine if a claim is misinformation
- Only posts with full agreement will be labeled as misinformation. Disagreements will be adjudicated by rater consensus after re-evaluating the claim. Continued disagreement will disqualify the claim from the dataset.
- After labeling the required number of claims, labels will be propagated back to the raw social media post where the claim originated.
- The final validation datasets will include raw social media with both misinformation and non-misinformation messages.

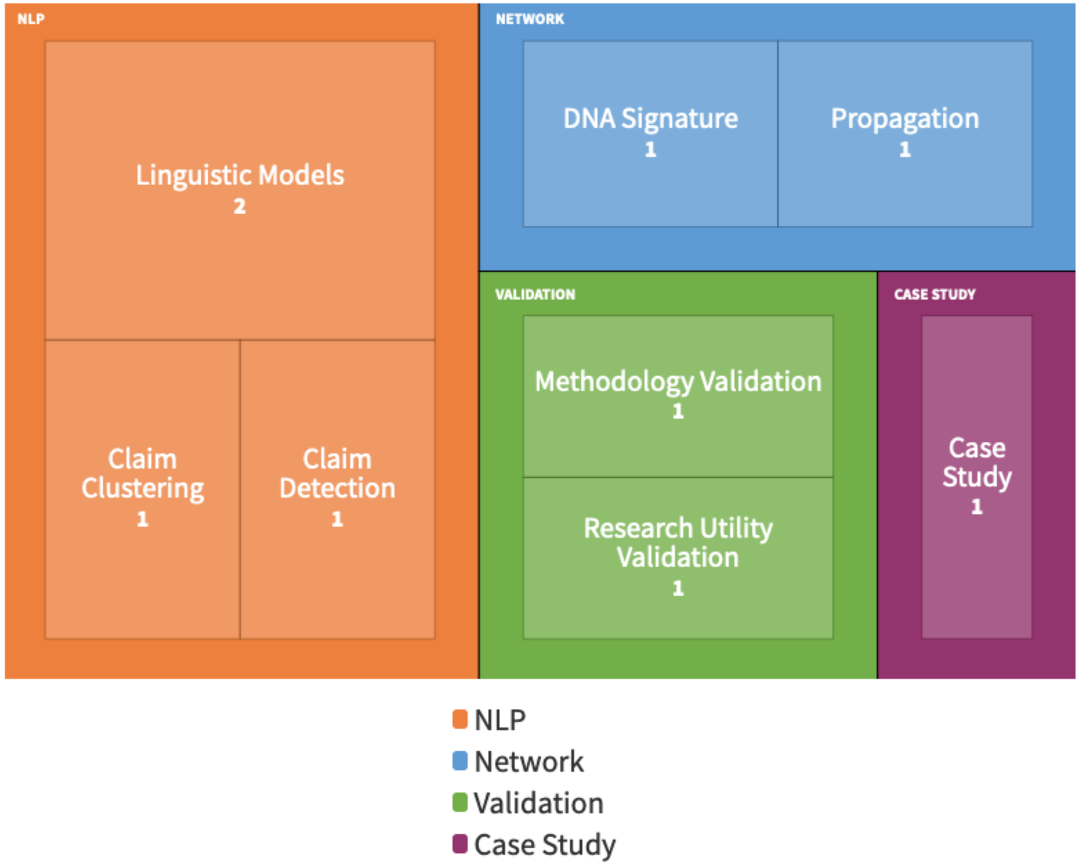


Platform	Topic	Data Size (Claims)	Have Data?	Misinformation Tagged
Twitter	COVID-19	250	Yes	No
	US Politics	250	Yes	No
	Russian Invasion	250	Yes	No
Reddit	COVID-19	250	Yes	No
	US Politics	250	Yes	No
	Russian Invasion	250	Yes	No
Telegram	COVID-19	250	Yes	No
	US Politics	250	No	No
	Russian Invasion	250	Yes	No
Facebook	COVID-19	250	No	No
	US Politics	250	No	No
	Russian Invasion	250	No	No
	Total	3,000		

*Note, 250 is **not** the total data size. Instead, this is the number of claims that will be tagged in each dataset as containing misinformation or not.

Research Roadmap (Workload)

- NLP models
  - Claim detection = 1 study
  - Claim clustering = 1 study
  - Linguistic models = 2 studies
    - Logical fallacy detection
    - Counterclaim detection
- Network Models
  - Propagation model = 1 study
  - DNA signature model = 1 study
- Validation
  - Methodology validation = 1 study
  - Research utility validation = 1 study
- Case Study = 1 study
- **Total work** = 9 studies



Research Roadmap (Timeline)

		Spring 24	Summer 24	Fall 24	Spring 25	Summer 25	Fall 25
Study	Data Tagging	🟧	🟩				
	Claim Detection		🟧	🟩			
	Claim Clustering		🟧	🟩			
	Linguistic Models			🟧	🟩		
	Propagation Model			🟧	🟩		
	Dynamic Network Model				🟧	🟩	
	Validation Studies					🟧	🟩
	Case Study						🟩

🟧	Study Start
🟩	Study End

- ***None of this work is complete***
  - Claim detection and clustering work is underway, Propagation, Linguistic Models, Dynamic Network model are in literature review stages

Limitations and Boundary Conditions: Language

- Only using English data or data translated into English
  - Better support for NLP methods and better sources on media reliability
  - Can expand to other languages in future as multilingual tooling develops
  - Must then focus on topics with misinformation targeting English speakers

Limitations and Boundary Conditions: Data

- Focus on text-based social media due to reliance on NLP methods
- Available data sources:
    - Telegram (data is accessible, but network features are unideal due to snowball sampling collection)
    - Reddit (API shut down, relying on existing or purchased data)
    - Twitter/X (API shut down, relying on existing or purchased data)
    - Facebook (API shut down, relying on existing or purchased data)
- Topic Generalizability
    - Due to the burden of data tagging, this study will only look at 3 topics
    - These topics were selected because they are diverse and distinct, but it is possible that this methodology will fail to generalize beyond these selected topics
    - Future work should validate the model’s utility when applied to additional topics

Limitations and Boundary Conditions: Types of Misinformation

- Cannot detect misinformation that doesn’t have some counter-conversation happening in the data
  - System is not meant to be a fact-checker, but is meant to find **relevant** misinformation
    - We expect that misinformation that is having an effect on the information environment will be met with counter points.
    - Misinformation that is having little effect on the information environment has less research value.
  - System is meant to enhance BEND analysis, which is applied in contested information spaces
    - Contested information spaces are likely to contain counter-conversation to misinformation claims.

Conclusion: Research Contributions

- Methodological contributions
  - Overall = an unsupervised methodology for misinformation detection using both linguistic and network features
  - Other contributions:
    - Improved multi-topic social media claim detection
    - Improved multi-topic claim clustering
    - Improved linguistic models for detecting counter-narratives and logical fallacies
    - Identification of dynamic network signatures of misinformation
    - Improved unreliable-source propagation in social media data
  - Datasets:
    - Claim detection data
    - Validation data
- Application contributions
  - Enhance the BEND framework by providing another lens for social cybersecurity analysis
  - Better understanding of misinformation's emergence and use in the information space