

Twitter User Geolocation Using Deep Multiview Learning

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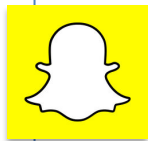
Social Networks and Location of Users



2.2B active users



330M active users



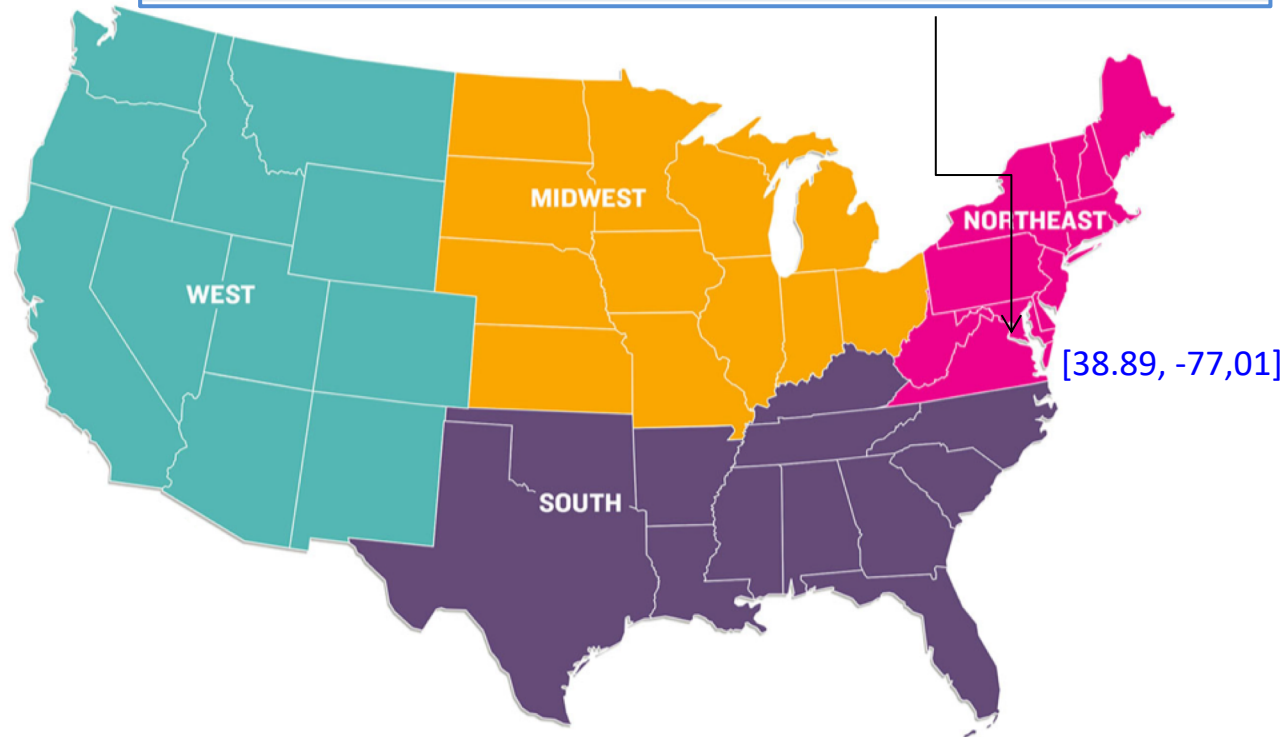
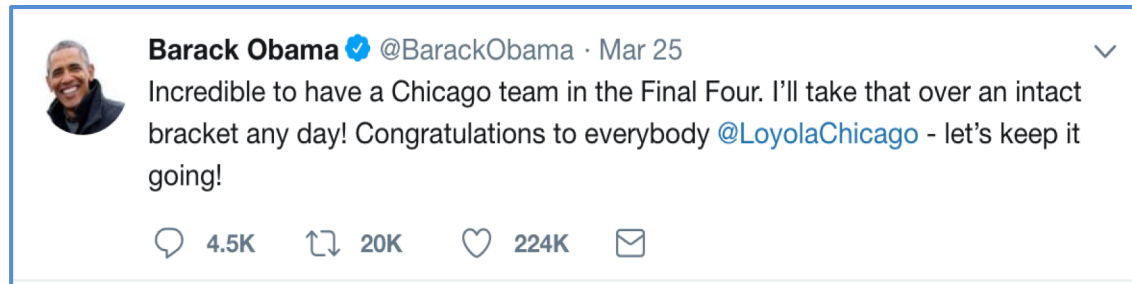
255M active users

- Location of users enable many applications
- User location profile information might be missed or ambiguous: e.g. “Small town”, “Everywhere”
- ~3% of tweets are geo-tagged [3]

Reference: <https://www.statista.com/statistics/272014/global-social-networks-ranked-by-number-of-users/>

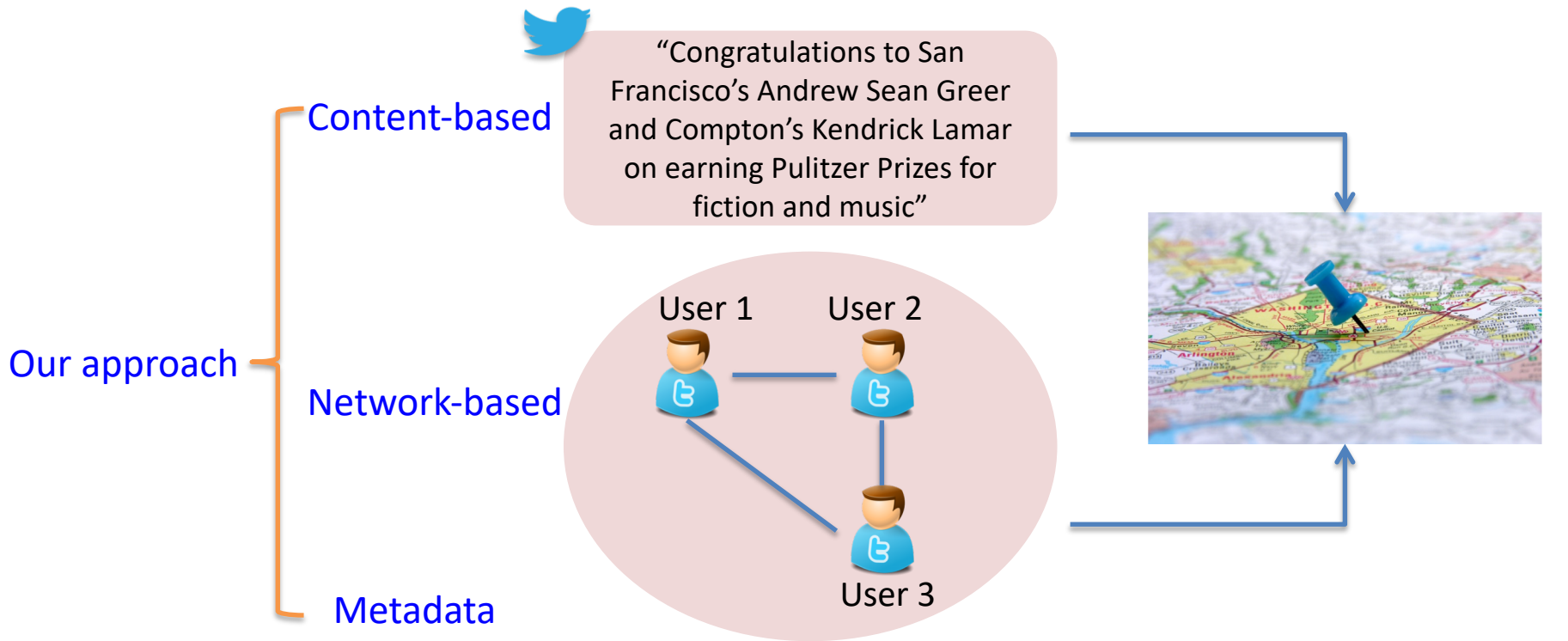
The Tasks of Twitter User Geolocation

- Region classification:
Northeast, Midwest, West,
and *South*
- State classification: *50 states*
- Geo-coordinates prediction: (*latitude,*
longitude)



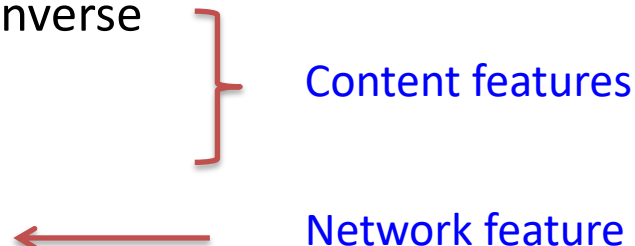
Region and state boundaries are from the US census shape files

Our Approaches

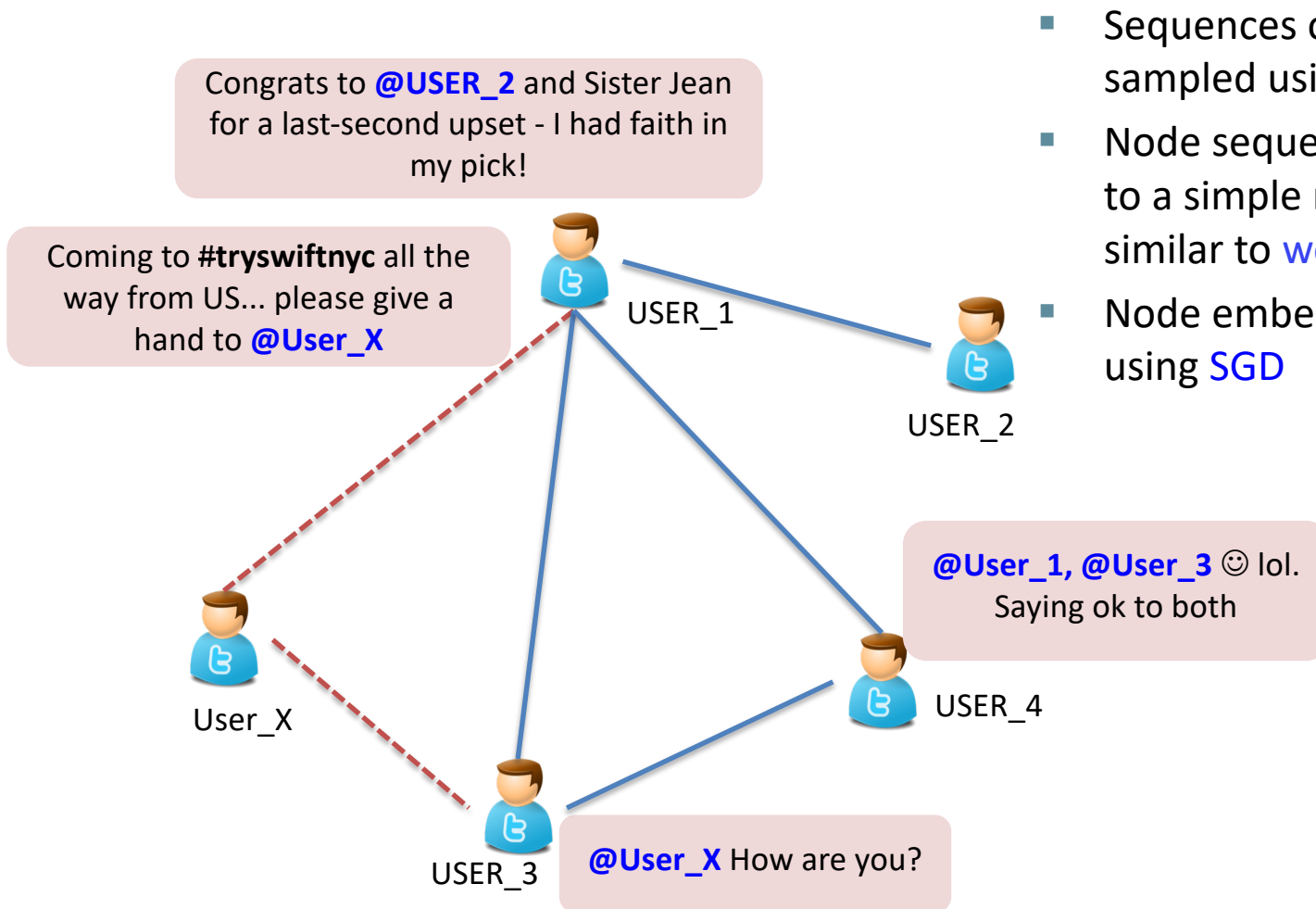


- **Content-based:** Tweets are used for location prediction
- **Network-based:** Online relationships (e.g. following, mentioning) are used for location prediction

Learning from Multiple Views

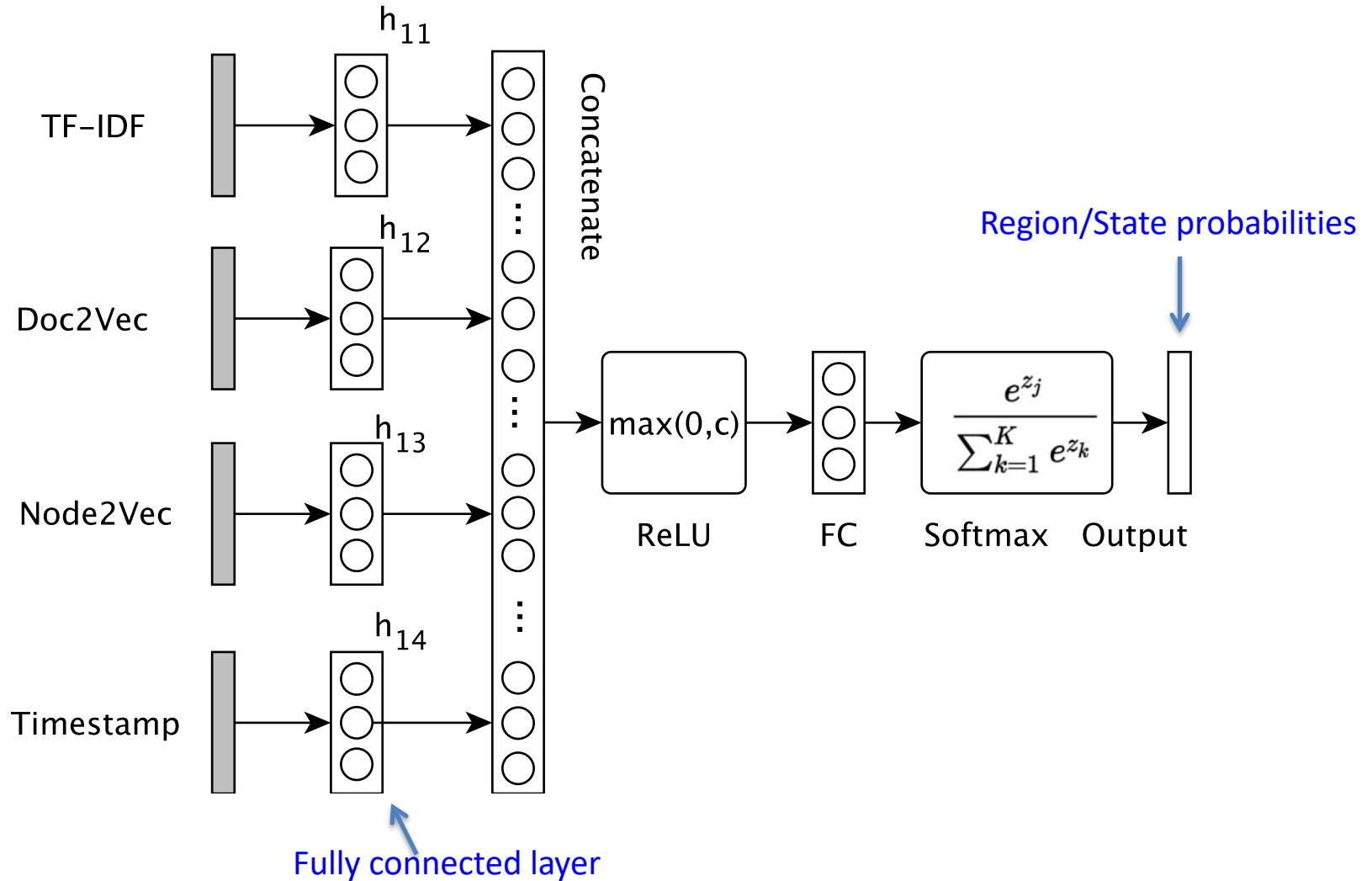
- Processing: Tweets from the same user are **concatenated** making up a **tweet document**
 - Feature extraction:
 - Individual word level: Term frequency-inverse document frequency (*TF-IDF*)
 - Semantic level: *Doc2vec*
 - User connection structure: *Node2vec*
 - Metadata: Posting *timestamps* of tweets
- Content features
- Network feature
- 

User Representation as Node Embedding



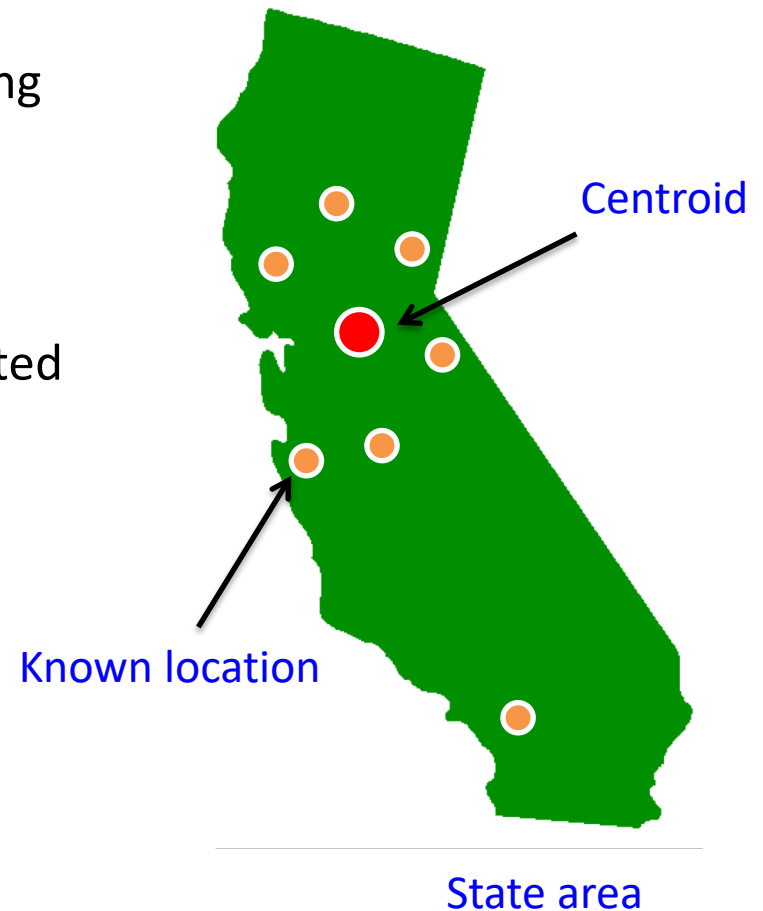
- Sequences of node indices are sampled using [Random Walk \[7\]](#)
- Node sequences are the input to a simple neural network similar to [word2vec \[8\]](#)
- Node embeddings are trained using [SGD](#)

MENET: Proposed Architecture



From Classification to Regression

1. Predict the state label
2. Predict geographical coordinates using the **centroid** of the state
3. State **centroid** = **median** {[latitude, longitude]}
4. The centroid coordinates are calculated from the geographical coordinates available in the training set



Performance criteria

- Region and state classification: **Accuracy** (%)
- Geographical coordinates prediction:
 - Mean distance error (km)
 - Median distance error (km)
 - Accuracy within 161 km (~100 miles) or **@161** (%)
- The distance between two locations is computed using the **Haversine** formula

$$a = \sin^2(\Delta\phi/2) + \cos \phi_1 \cdot \cos \phi_2 \cdot \sin^2(\Delta\lambda/2)$$

$$c = 2 \cdot \operatorname{atan2}(\sqrt{a}, \sqrt{1-a})$$

$$d = R \cdot c$$

ϕ : Latitude

λ : Longitude

R: The Earth's radius

Experimental Results

Table 1. Region and state [classification](#) result on GeoText^[1] and UTGeo2011^[4]

	GeoText		UTGeo2011	
	Region (%)	State (%)	Region (%)	State (%)
Eisenstein <i>et al.</i> [1]	58	27	N/A	N/A
Liu & Inkpen [2]	61.1	34.8	N/A	N/A
Cha <i>et al.</i> [3]	67	41	N/A	N/A
MENET	76	64.8	83.7	69

- 9% improvement for region classification
- 23.8% improvement for state classification

Experimental Results

Table 2. [Geo-coordinates prediction](#) on GeoText^[1] and UTGeo2011^[4]

	GeoText			UTGeo2011		
	mean (km)	median (km)	@161 (%)	mean (km)	median (km)	@161 (%)
Eisenstein <i>et al.</i> [1]	900	494	N/A	N/A	N/A	N/A
Roller <i>et al.</i> [4]	897	432	35.9	860	463	34.6
Liu and Inkpen [2]	855.9	N/A	N/A	733	377	24.2
Cha <i>et al.</i> [3]	581	425	N/A	N/A	N/A	N/A
Rahimi <i>et al.</i> (2015) [5]	581	57	59	529	78	60
Rahimi <i>et al.</i> (2017) [6]	578	61	59	515	77	61
MENET	570	58	59.1	474	157	50.5

Conclusion

- Twitter user geo-location is **challenging** due to noisy data.
- Combine the **content** and **network** features can improve the geo-location accuracy.
- **Multi-view learning** can exploit different views of Twitter data for location prediction.
- The proposed architecture can be **extended** with different types of features or by adding more hidden layers.
- The **distribution** of Twitter users will be considered in the future work.

References

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References

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Thank you for your attention !

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