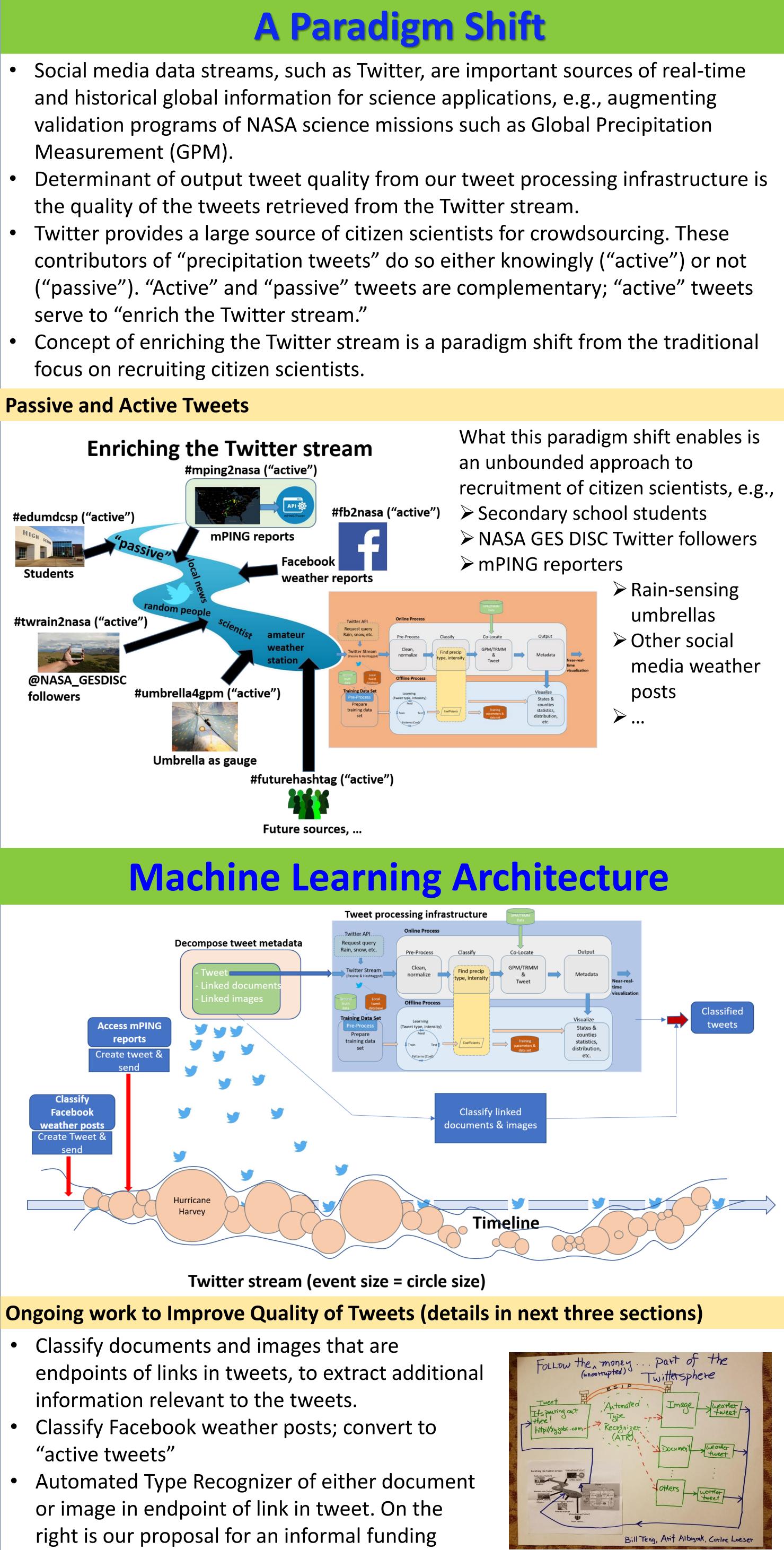




AGU December 2018 NH43B-2988



opportunity at the ESIP 2018 Summer Meeting.

Enriching the Twitter Stream Increasing Data Mining Yield and Quality Using Machine Learning

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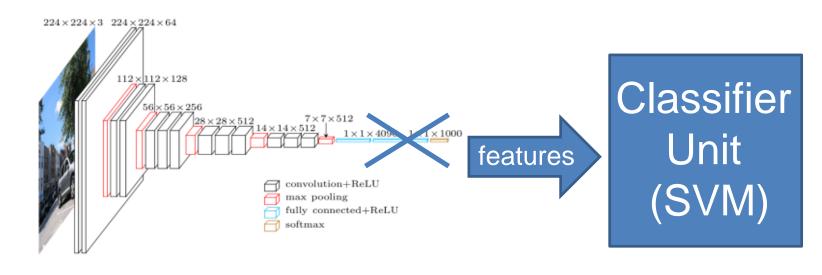
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Classifying Tweet-linked Images (Corcoran)

Construct classifier to analyze images for precipitation-related information (e.g., is there rain in the image? is it a forecast map?)

A Transfer-Learning Approach

- Deep learning models, particularly Convolutional Neural Networks (CNN), have been shown to be very effective for large-scale image recognition and classification • Because a large number of labeled images is required to develop CNN, doing so
- from scratch would be very costly in compute and time resources. • **Transfer Learning** takes advantage of pre-trained models as a starting point, thus mitigating the cost of model development for the current task. These reused models are, in effect, feature extractors, the outputs from which then become inputs for training smaller, more manageable classifiers.
- For the current task, we used VGG-16¹ as the feature extractor, by removing the final fully connected layers, and trained a linear support vector machine (SVM) to output the final classification (i.e., "precipitation" and "not-precipitation").



Basic structure of our model: VGG-16 architecture² (left); fully connected layers removed ("X"); extracted features with which to train classifier (for current task, SVM).

> Confusion matrix of classification on a 90-image test set, split into two target categories, "precipitation" and "not-precipitation."

Classifying Tweet-linked Documents (Wang)

Use Hierarchical Attention Network (HAN)-based model to classify tweet documents, i.e., precipitation occurrence, type, and intensity, at given locations and times.

Architecture: Hierarchical Attention Networks³

Word/Sentence Encoder – Embed words to vectors through embedding matrix; apply bidirectional GRU⁴ to obtain **representative, contextual** hidden annotations of words/sentences.

Word/Sentence Attention – Combine learned measure of importance with contextual word/sentence annotations; more relevant words have greater weighting, and vice versa.

Word Encoder -> Word Attention -> Classification – Softmax*, categorical cross-entropy# Sentence Encoder -> Sentence Attention -> *Regression* – Softmax, mean squared error Classification/Regression *Softmax – reduces influence of extreme values by constraining data into the range 0-1 before classification.

*Categorical cross-entropy – used as final layer in classifying data to predefined classes. **Results / Alternate Model Comparisons**

Data Type	Accuracy
Precipitation Occurrence (Yes/No)	83.6%
Precipitation Type (Rain/Sleet/Snow/Null)	77.4%
Precipitation Intensity (mm/hr)	74.2% (±1.5 mm/hr)

Model Attention Weight Visualizations

Model places greater importance on darker words during classification / regression.

Example 1: At 9:04 AM, Deerfield [Franklin Co, MA] HAM RADIO reports SNOW of 3.00 INCH #BOX <u>https://t.co/123</u>

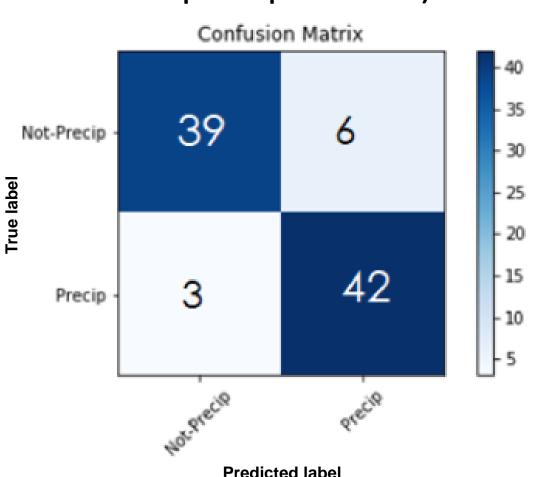
Word-level Attention Weights Visualization: at <time>, deerfield [franklin co , ma] <allcaps>ham radio </allcaps> reports <allcaps> snow </allcaps> of <number> <allcaps> inch </allcaps> </ashtag> box </hashtag> <url>

Example 2: It's chilly outside but so beautiful! Enjoy the snow day 🍪 #staywarm #snowmageddon... https://t.co/123 Sentence-level Attention Weights Visualization

it 's chilly outside but so

enjoy the snow day 🎇 stay warm Word-level Attention Weights Visualization:

it 's chilly outside but so beautiful! snowmageddon</hashtag>... <url>



Example 3: All this snow has us wishing for summer! Sippir on our beachy 🖗 Coco Rooibos Chai this morning.. https://t.co/123

Sentence-level Attention Weights Visualization all this snow has us wishing for sipping on our beachy 🌴 coco rooibos chai this

Word-level Attention Weights Visualization: all this snow has us wishing for summer!

April 6 at 11:06am - @ take look these The NWS released a set of new (experimental) graphics this year for winter weather events. One of the main cogs in this experimental whee two graphics has been the "expected" and "potential" graphics for snowfall. In theory makes total sense to display these two things graphically - people want and need to know! But in practice, it really appears to be a bit of a expected potential for ke a look at these two graphics - expected and potential - for tomorrows dmv storm orrow's DMV storm, released today at 9:40am (point being - this is SH info from the NWS) and decide for yourself. Does this make any Cleaning a released nse? Does it inform you better than before or simply add to the fusion? Seriously, let's face it - every storm has POTENTIAL to do any token today 940am point umber of things (and we, admittedly, love to present and discuss potential)...but when potential is placed in a context that is directly elative to expected, it blends in too much for most (even those of us who being this stare at this informational morass 24/7) to really feel informed about the future with any confidence. Why not just make every storm's forecast 0 fresh info from nws 48" and be done with it (with a BUST-EXPECTED-BOOM layering of the 4cast cake to really cover all bases 14 th 19??? and decide for yourself Stay tuned for updates from DMV Weather on this upcoming storm Based on these NWS graphics, it might just rain a little or it totally could snow a lot, so we're thinking about changing our "one-and-only-one official forecast" to 0-754" to match the guidance and ensure accuracy.

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Classifying Facebook Posts (Maksumov) Construct classifiers to label posts on Facebook weather pages as precipitation related (e.g., is this post suggesting that it's snowing right now?) **Data Preprocessing: Cleaning Facebook Posts** April 6 at 11:06am - 13 Stay tuned for updates from DMV Weather on this upcoming storm Original Facebook posts scraped using Python program by minimaxir⁵ **Creating Feature Vectors: TF-IDF (Term Frequency-Inverse Document Frequency)** For each word in a token, multiply together: • # times the word appears in the token • Log (# tokens / # tokens with the word)

Creating a Classifier: Naive Bayes Algorithm

Best label maximizes chances of finding label in training set and finding token's words in label

Results: Classifying the Token's Words

- More data in training set -> greater label accuracy
- 300+ training data -> about 80% correct classification

- tweets from "active" participants.
- them to "active" tweets.

References

¹VGG-16 (Visual Geometry Group-16; also OxfordNet), https://gist.github.com/baraldilorenzo/07d7802847aaad0a35d3 ²Image of VGG-16 architecture, <u>https://blog.heuritech.com/2016/02/29/a-brief-report-of-the-heuritech-</u> deep-learning-meetup-5/

HLT, San Diego, 1480-1489.

arXiv:1409.0473 [cs.CL].

⁵Woolf, M. (minimaxir), 2017, Facebook page post scraper, <u>https://github.com/minimaxir/facebook-page-</u> post-scraper.

Acknowledgments: This work was supported, in part, by

GPM validation."

> NASA Goddard's Office of Education, for the internship of Daniel Maksumov. > NASA GES DISC, for the internship of Sky Wang. > ADNET Systems, Inc., for the internship of John Corcoran



Converted, messy text data -> numerical data to analyze

 $c_{NB} = \underset{c \in C}{\operatorname{argmax}} P(c_j) \prod P(x \mid c)$

1 day data		Naive bayes scores								
2 day data		90								
• 3 day data		85		_						
	Test set 2	80						•		
		75		_			_			
		70			•		•			
		65				•	•			
		60								
		55								
		50								
		50	C	60	-	70	8	0	90	
		Test set 1								

Summary

• Paradigm shift from a focus on recruiting citizen scientists to enriching the Twitter stream enables an unbounded approach to recruitment.

Output tweet quality and quantity from our tweet processing infrastructure is increased by complementing "passive" tweets from the Twitter stream with

Ongoing work to improve quality of tweets include (1) classifying documents and images that are endpoints of links in tweets, to extract additional information relevant to the tweets and (2) classifying Facebook weather posts and converting

³Yang et al., 2016, Hierarchical attention networks for document classification, in Proc. 2016 Conf. NAACL-

⁴Bahadanau et al., 2014, Neural machine translation by jointly learning to align and translate,

> NASA Citizen Science for Earth Systems Program, for the project, "Mining Twitter data to augment NASA