

How Emotional are you?

Neural Architectures and Transfer Learning for Emotion Intensity Prediction in Microblogs

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Anger



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- **Predict:** Emotional Intensity
(Annotated Intensity (gold label): 0.833)
- This is the EmoInt shared task ([1]) conducted at WASSA 2017.



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Which tweet expresses **MORE** sadness?

‘When you lose somebody close to your heart you lose yourself as well. Crying my heart out!!!’



‘All friends are out of town. Feeling a bit lonely...’



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Which tweet expresses **MORE** sadness?

‘When you lose somebody close to your heart you lose yourself as well. Crying my heart out!!!’  

‘All friends are out of town. Feeling a bit lonely...’ 



Motivation

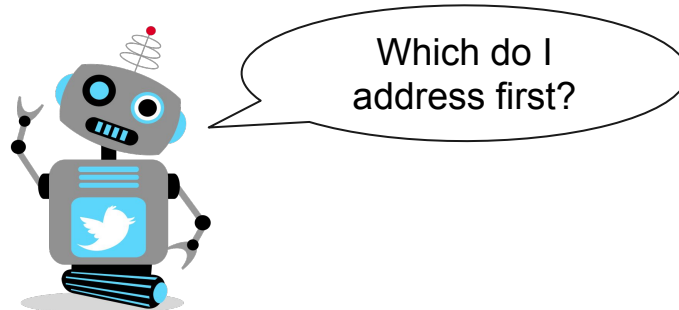
- Tweeted reviews of a product/service.

Motivation

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Angry Rant 1

Angry Rant 2

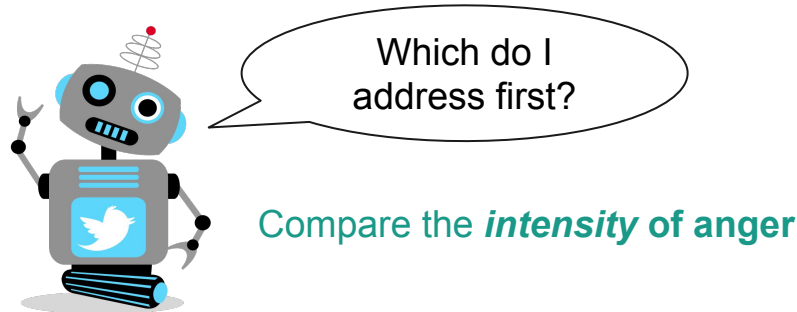


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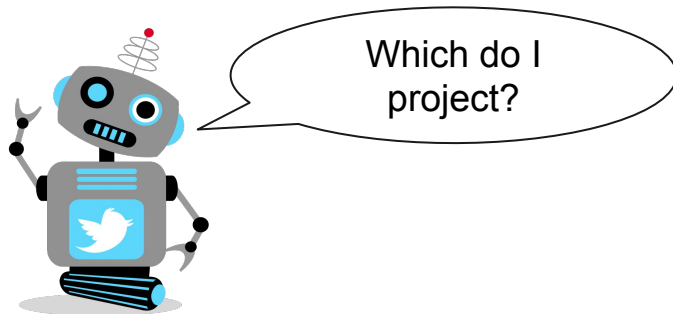
Compare the *intensity* of anger

Motivation

- Tweeted reviews of a product/service.

Glowing Review 1

Glowing Review 2

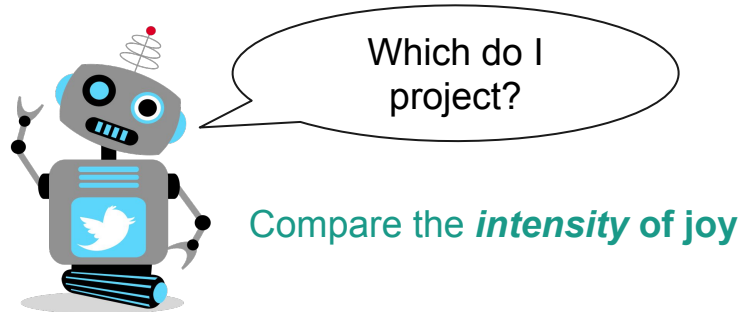


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Glowing Review 1

Glowing Review 2





Dataset

Link: <http://saifmohammad.com/WebDocs/EmoInt\%20Train\%20Data/>

Emotion	Train	Dev	Test	All
Anger	857	84	760	1701
Fear	1147	110	995	2252
Joy	823	74	714	1161
Sadness	786	74	673	1533
All	3613	342	3142	7097



Approaches/Models

1. LE-PC-DNN

2. LE-PC-DMTL

3. LE-PC-DMTL-EI



**Deep Multi-Task
Learning based**



LE-PC-DNN model

It stands for **L**exicon + **E**moji based features used in a **P**arallel **C**ombination of **D**eep **N**eural **N**etworks



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A neural network based architecture combining -

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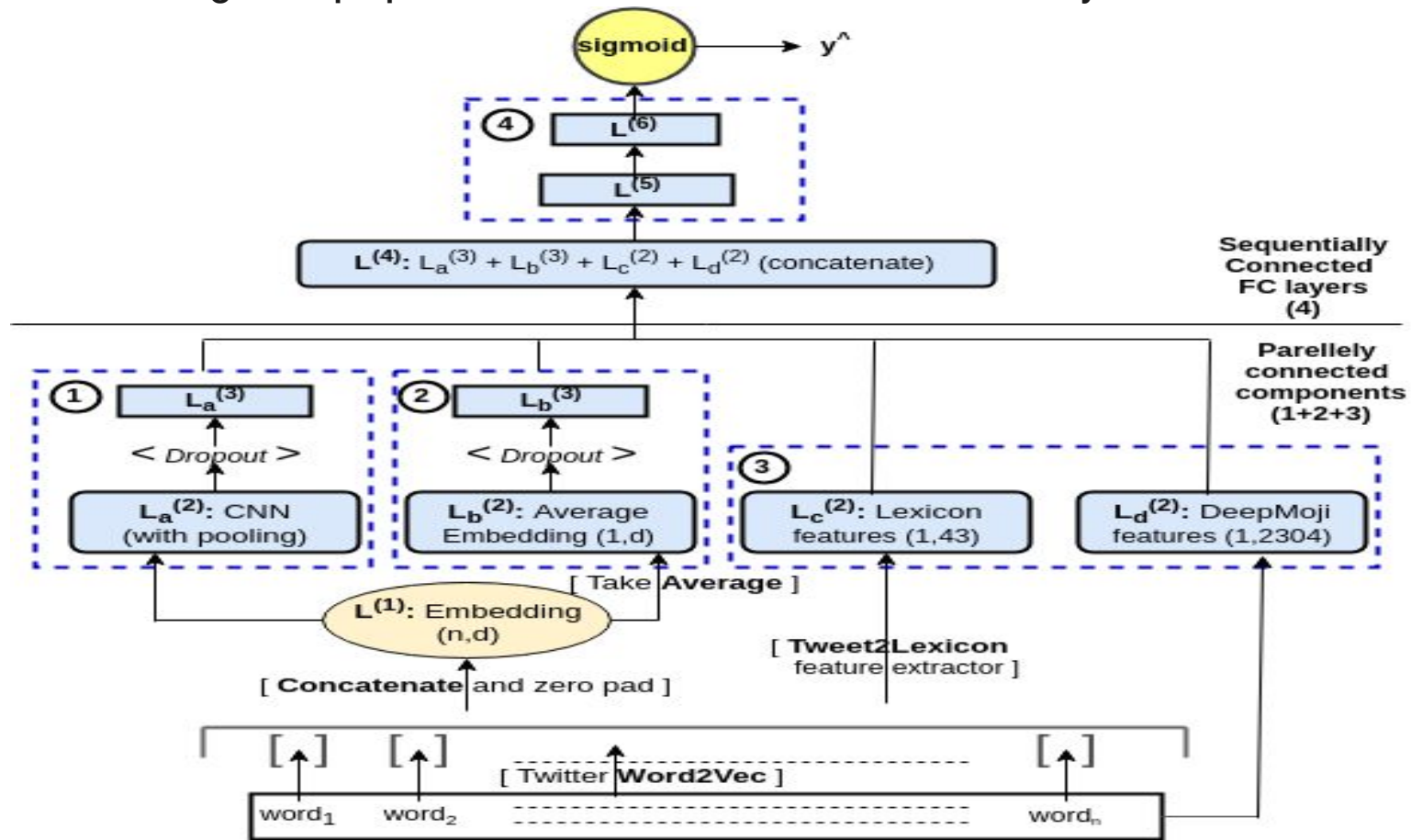
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- Fully-connected layers
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combined in a **non-sequential or parallel** manner!

Fig 1: Our proposed LE-PC-DNN model for Emotion Intensity Prediction

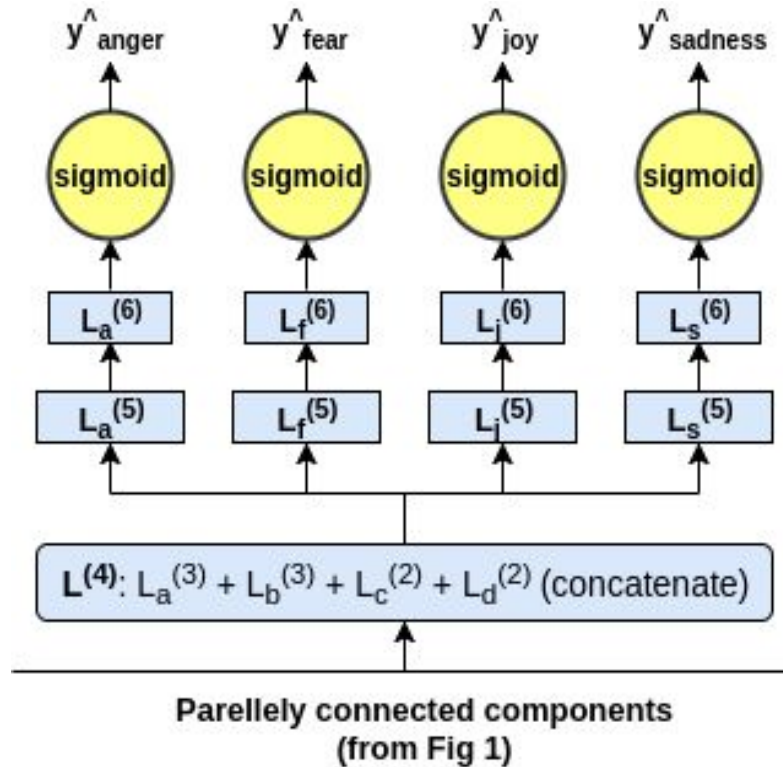




LE-PC-DMTL model

It stands for **L**exicon + **E**moji based features based **P**arallel **C**onnected **D**eep **M**ulti-**T**ask **L**earning neural network.

Fig 2a: Our proposed LE-PC-DMTL model for Emotion Intensity Prediction





LE-PC-DMTL-EI model

It stands for **L**exicon + **E**moji based features based **P**arallel **C**onnected **D**eep **M**ulti-**T**ask **L**earning neural network optimized for the task of **E**motion **I**ntensity detection.

Allows grouping of similar emotions and separate branching of unrelated tasks.

Fig 2: Our proposed LE-PC-DMTL and LE-PC-DMTL-EI models for Emotion Intensity Prediction

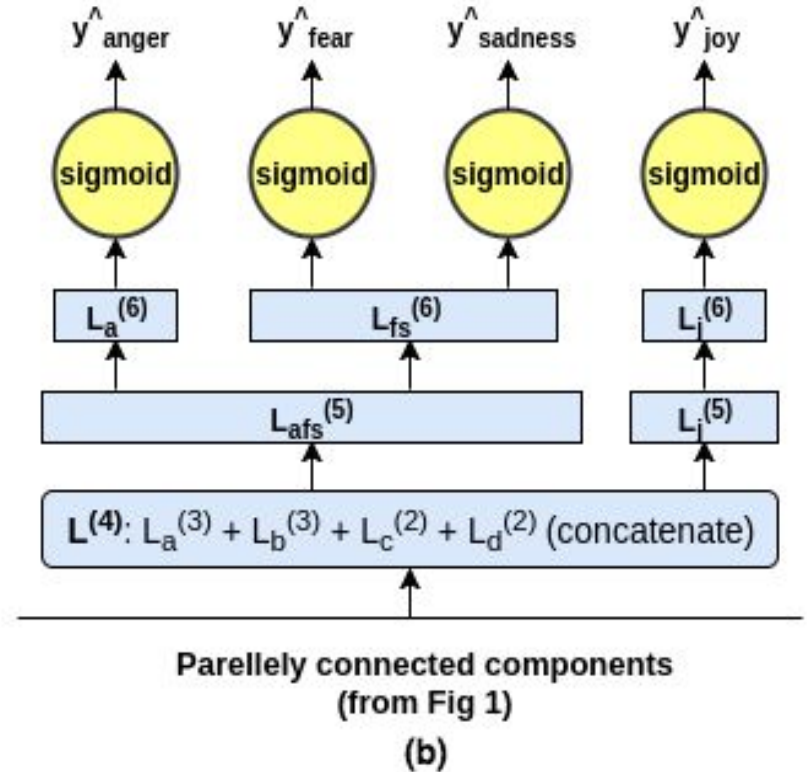
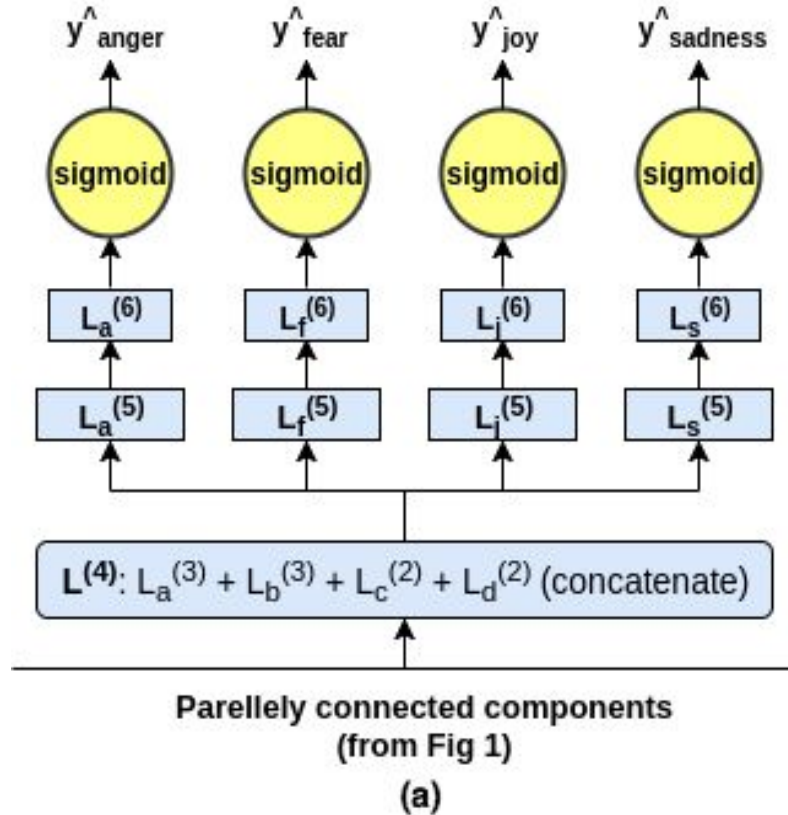
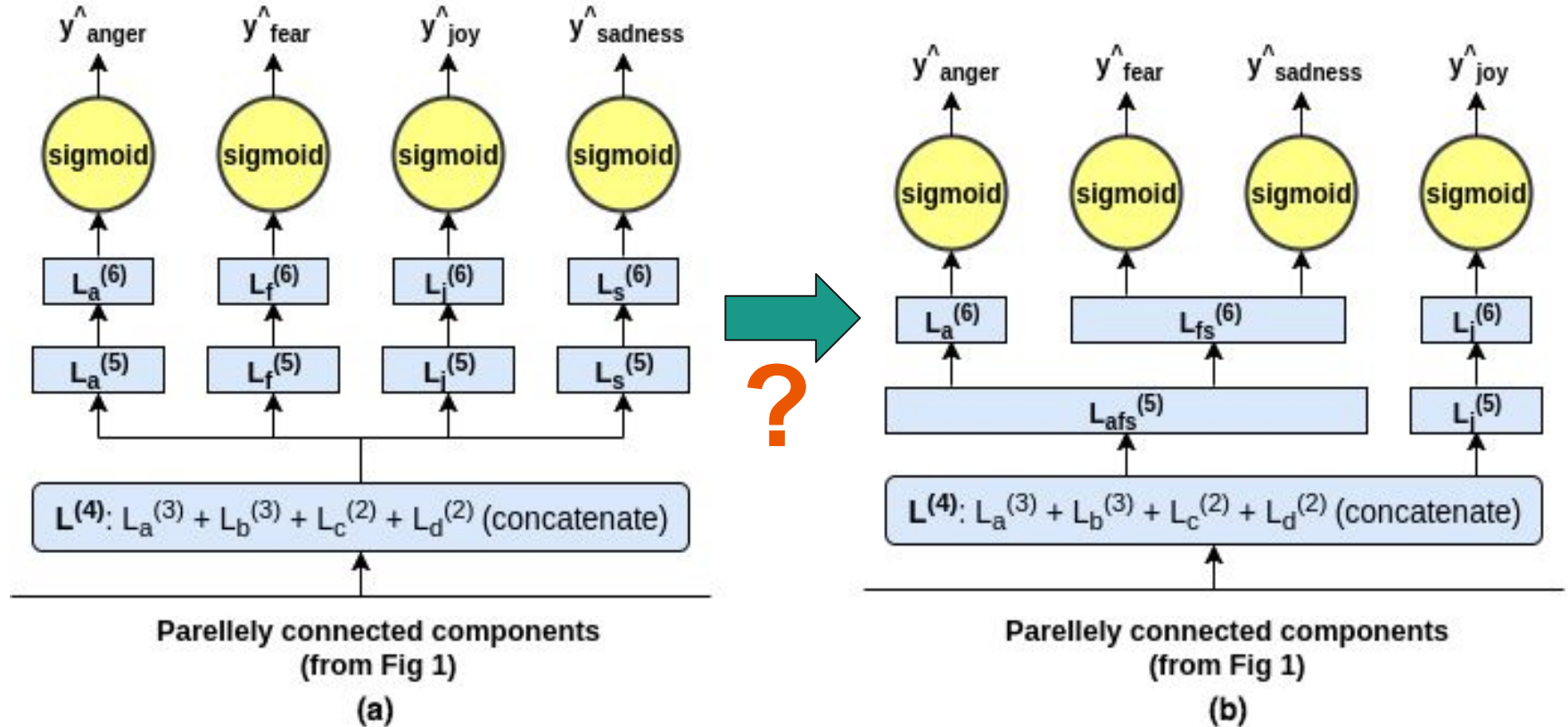
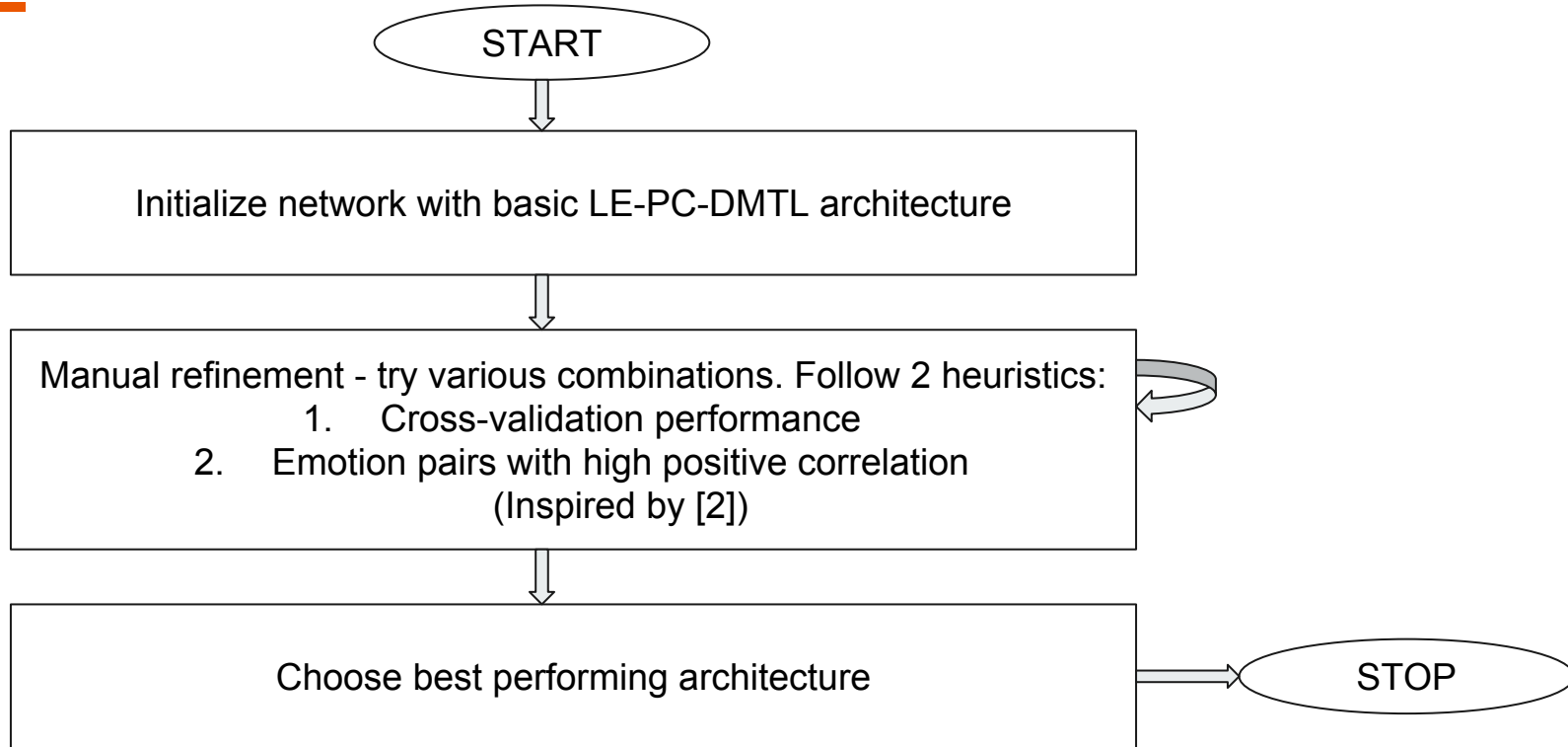


Fig 2: Our proposed LE-PC-DMTL and LE-PC-DMTL-EI models for Emotion Intensity Prediction



LE-PC-DMTL-EI : Learning the network architecture





Implementation Details

Word Embeddings

- Publicly available pre-trained word embeddings called the Twitter word2vec model.
- Trained on 400 million tweets using the word2vec approach.
- The large number of tweets in training data makes it a better choice than others available

Pre-processing

- Removal of URLs and user mentions.
- Stripping punctuations from word boundaries.
- Hashtag segmentation ('#wearethebest' to 'we are the best') and elongation removal ('gooooooooood' to 'good').



Implementation Details

Network Hyper-Parameters and Architecture Settings

- 7-fold cross validation on the combined training and validation sets.
- Changed various network hyperparameters like number of layers, output dimensionality, the type of pooling for CNNs (max versus average) and dropout value.
- Tried various RNN architectures including LSTM, Bidirectional LSTM and Gated Recurrent Units (GRU).



Implementation Details

Training

- Minimized the Mean Absolute Error between the actual and predicted intensity values.
- Optimize by back-propagating through layers via Mini-batch Gradient Descent.
- Use a batch size of 8, 25-30 training epochs and Adam optimization algorithm, with parameters set as $\alpha=0.001$, $\beta_1=0.9$, $\beta_2=0.999$ and $\epsilon=10^{-9}$



Evaluation

- **Pearson correlation coefficient (r)** between gold ratings and predicted output intensities.
- Was used in the EmoInt shared task.



Evaluation

Baseline systems to benchmark our results -



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- **Weka**: EmoInt baseline. ([3])



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- **Weka**: EmoInt baseline. ([3])

(we also use Two of the top performing systems in the shared task)

- **Prayas**: Previous state-of-the-art. ([4])
- **IMS**: Rank #2 in EmoInt. ([5])

Results (Pearson Correlation %)



Emotion	LE-PC-DNN	Prayas	IMS	Weka	LE-PC-DMTL-EI	LE-PC-DMTL	MTL (Prayas)
Anger	0.767	0.765	0.767	0.639	0.745	0.731	0.645
Fear	0.791	0.732	0.705	0.652	0.773	0.755	0.677
Joy	0.803	0.762	0.726	0.654	0.785	0.758	0.654
Sadness	0.803	0.732	0.690	0.648	0.808	0.786	0.672
Average	0.791	0.747	0.722	0.648	0.778	0.758	0.662

State-of-the-Art Performance

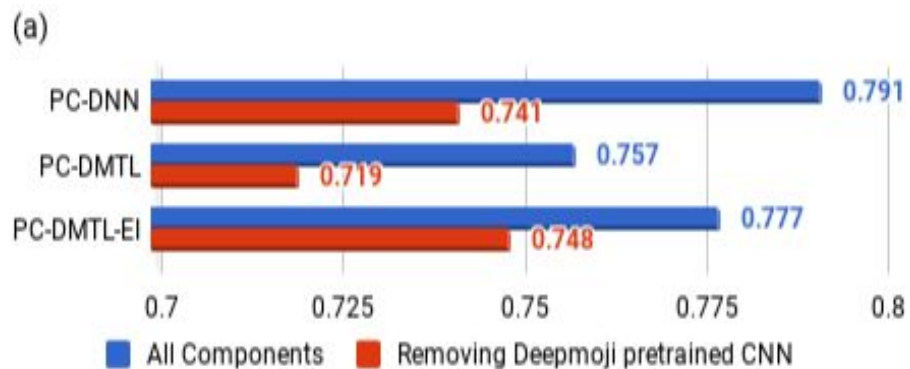
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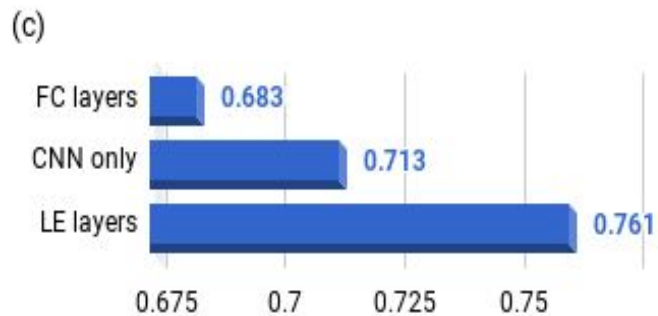
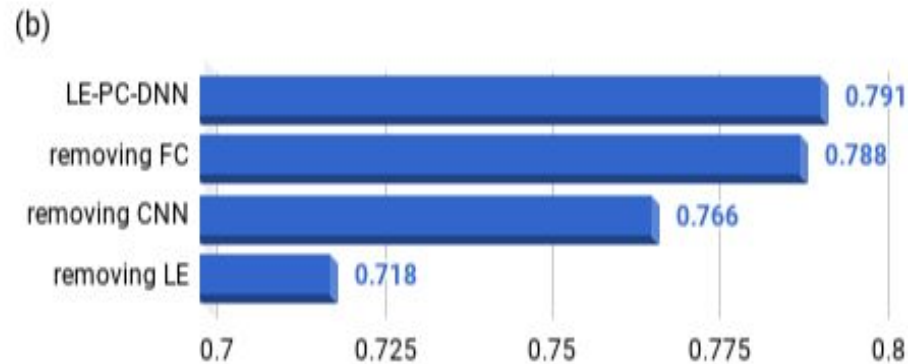
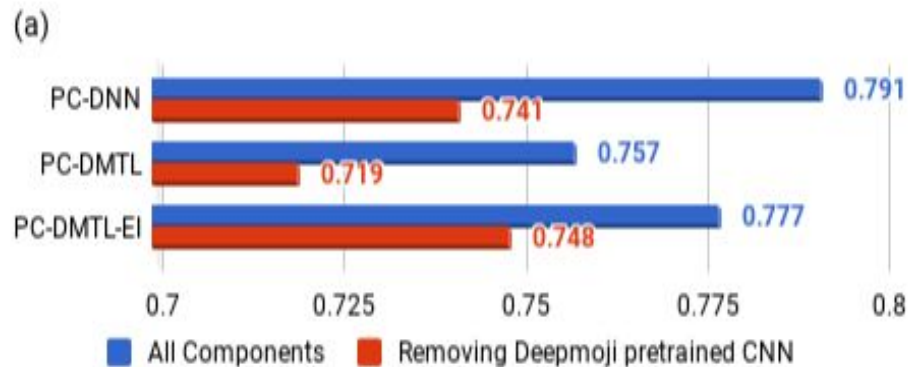
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Multi-Task Learning for Emotion Intensity prediction

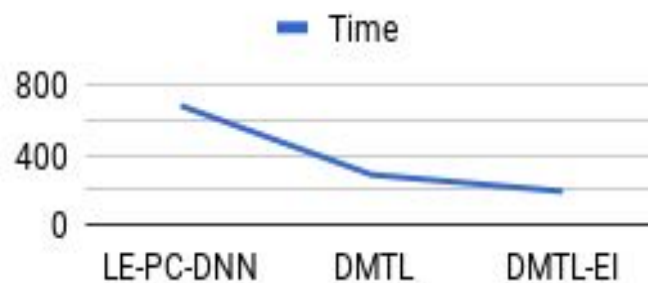
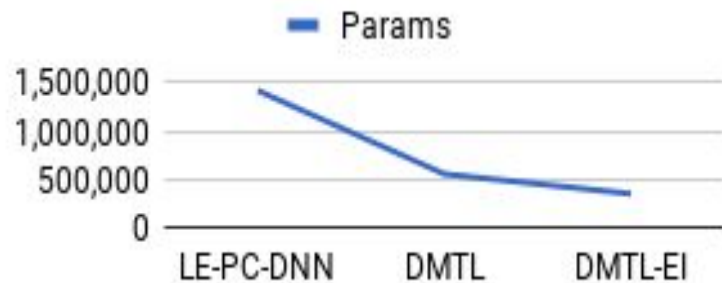
Ablation Tests



Ablation Tests



Practical Benefits of Multi-Task Learning

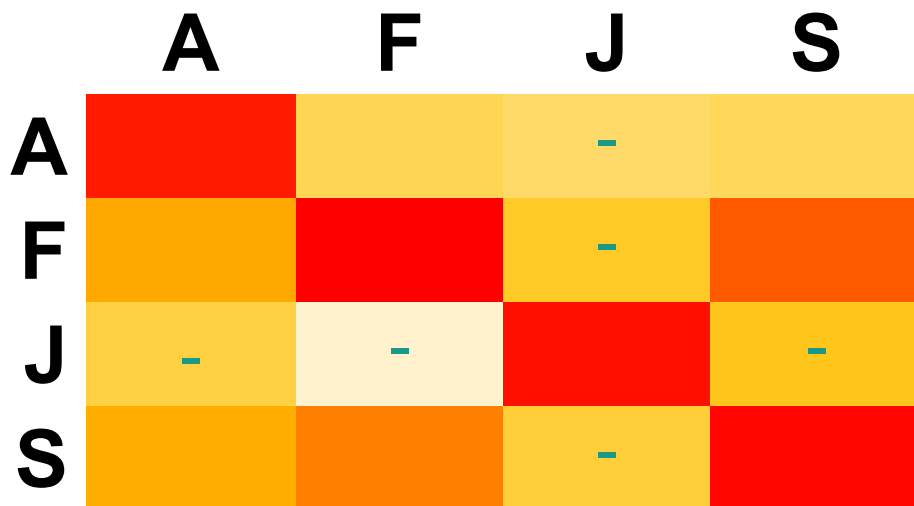




Pairwise Correlation between Emotions

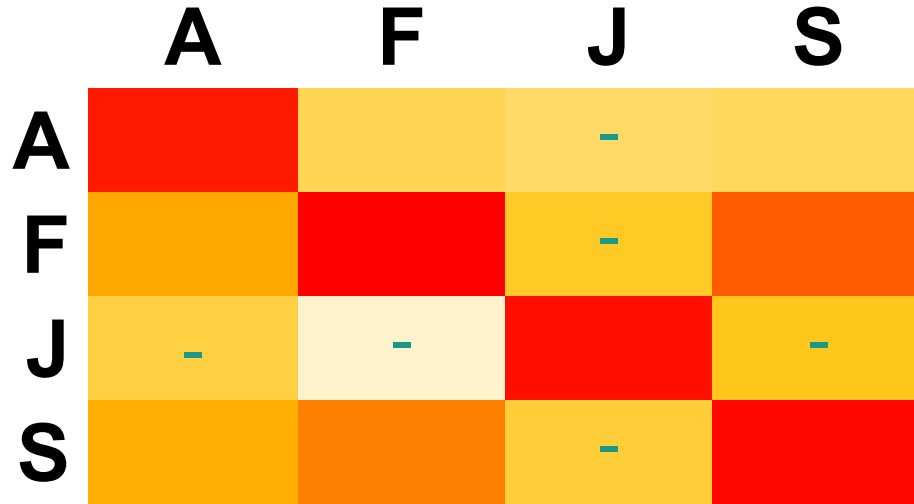
1. Training on One Emotion and Testing on Another
2. Training on a Combined Dataset of Two Emotions and Testing on Both of them

Training on One Emotion and Testing on Another



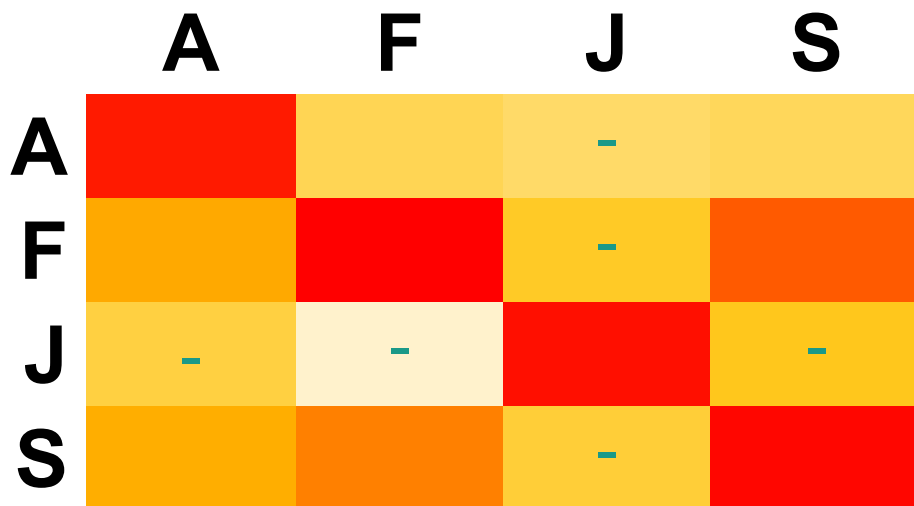
	A	F	J	S
A			-	
F			-	
J	-	-		-
S			-	

Training on One Emotion and Testing on Another



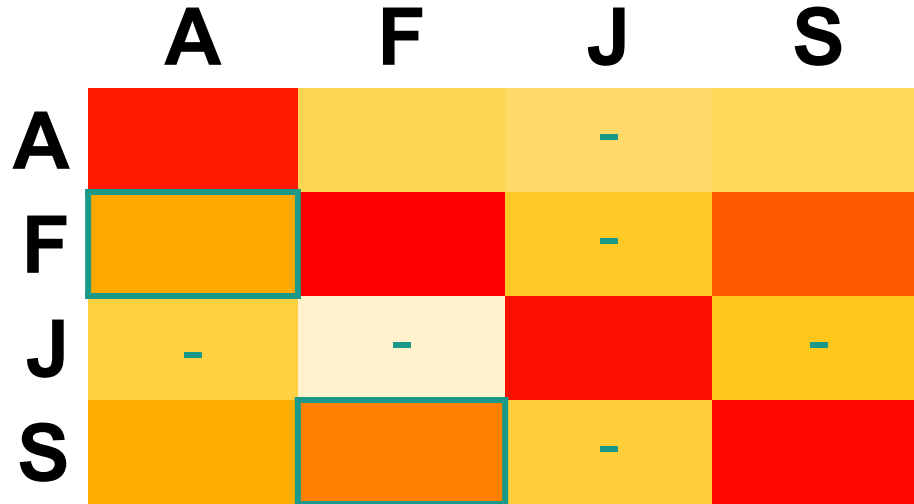
Significant correlation between all emotions (0.297 to 0.766)

Training on One Emotion and Testing on Another



Correlations are asymmetric

Training on One Emotion and Testing on Another



Fear and Sadness show highest correlation

Error Analysis



Tweet	Emotion	Actual Intensity	Predicted Intensity
Oi @THEWIGGYMESS you've absolutely fucking killed me.. 30 mins later im still crying with laughter.. Grindah.. Grindah...hahahahahahaha	Joy	0.846	0.469

Intensity Conveyed by Phrases, not Words

Error Analysis



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People are #hurt and #angry and it's hard to know what to do with that #anger Remember, at the end of the day, we're all #humans #bekind	Anger	0.25	0.568

Incorrect Modeling of the Full Tweet Context

Error Analysis



Tweet	Emotion	Actual Intensity	Predicted Intensity
T minus 10 hours till I meet with a designer who wants me to model his new fashion line !!!	Fear	0.667	0.291
Ibiza blues hitting me hard already wow	Sadness	0.833	0.447

Context Outside the tweet

Error Analysis



Tweet	Emotion	Actual Intensity	Predicted Intensity
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<u>Ibiza blues</u> hitting me hard already wow	Sadness	0.833	0.447

Metaphors



Future Work

- Topic Modeling



Future Work

- Topic Modeling
- Link to real-world applications (ranking product reviews)



References

1. Saif M. Mohammad and Felipe Bravo-Marquez. 2017b. WASSA-2017 shared task on emotion intensity. In Proceedings of the Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis (WASSA), Copenhagen, Denmark.
2. Lu, Yongxi, et al. "Fully-adaptive Feature Sharing in Multi-Task Networks with Applications in Person Attribute Classification." *CVPR*. Vol. 1. No. 2. 2017.
3. Saif M Mohammad and Felipe Bravo-Marquez. 2017a. Emotion intensities in tweets
4. Goel, Pranav, et al. "Prayas at emoint 2017: An ensemble of deep neural architectures for emotion intensity prediction in tweets." *Proceedings of the 8th Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis*. 2017.
5. Maximilian Koper, Evgeny Kim, and Roman Klinger. 2017. Ims at emoint-2017: Emotion intensity prediction " with affective norms, automatically extended resources and deep learning. In Proceedings of the 8th Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis, pages 50–57.



Thank You

- Our code can be found at <https://github.com/Pranav-Goel/Neural Emotion Intensity Prediction>.
- Please feel free to reach out with queries to us at pranav.goel.cse14@iitbhu.ac.in, and devang.kulshreshtha.cse14@iitbhu.ac.in.