Empirical Study on Transfer Learning for Text Classification

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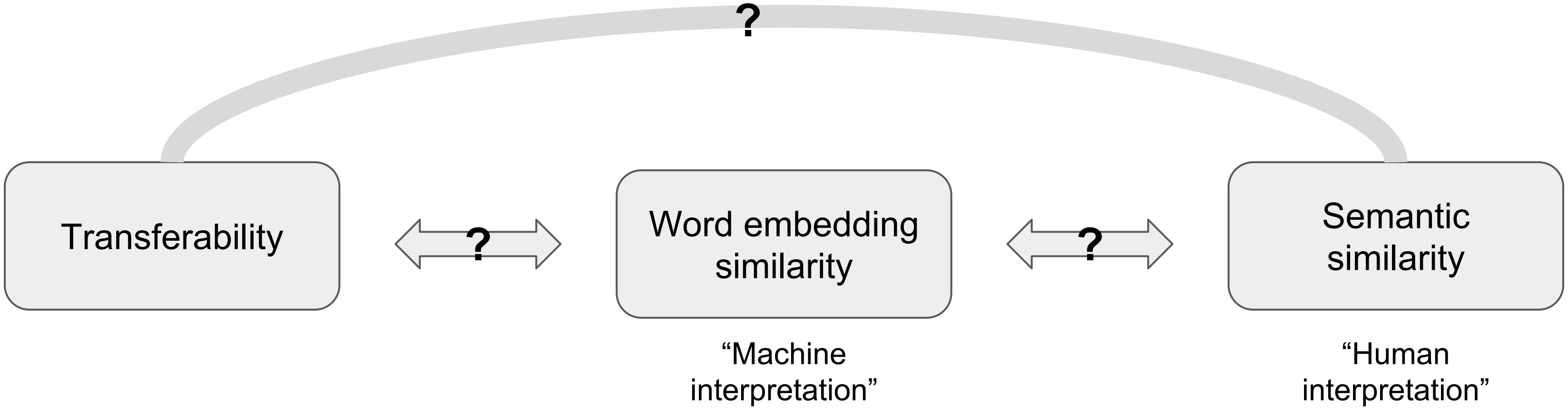
Motivation

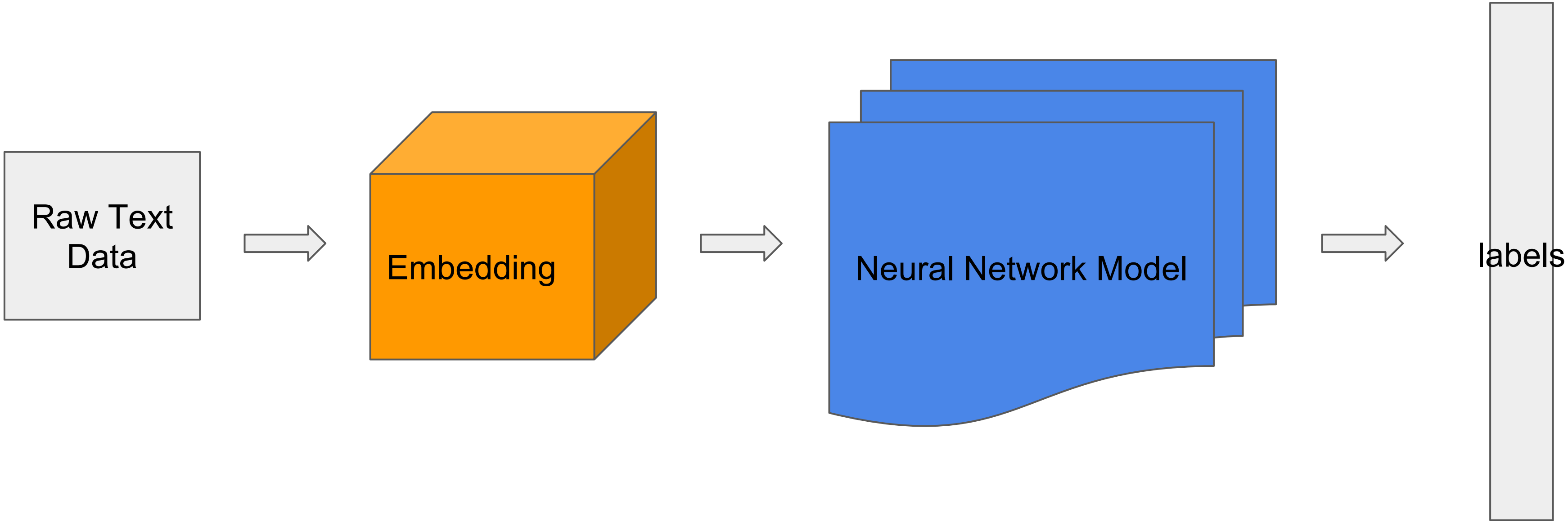
- Apollo
  - Entity classification based on news articles
  - Need rich historical data for training
  - How to make prediction if new entities or a new articles present?

- Transfer learning is important in many domains
  - Computer vision, reinforcement learning, natural language processing...

We are interested in...



Text classification task



Data

- StackExchange Questions (SE)

id	**title**	content	**tag**

- Sentence Involving Compositional Knowledge (SICK)

id	sent_1	sent_2	sim	label
1	A group of kids is playing in a yard and an old man...	A group of boys in a yard is playing and a man...	4.5	NETURAL
2	An elderly man is sitting on a bench	An old person is sitting on a bench	4.6	ENTAILMENT
3	A cat is stuck on a moving ceiling fan	There is no cat swinging on a fan	2.8	CONTRADUCTION

Embedding Methods

- W2V
  - Google pre-trained model (*google-w2v*)
  - Self-pretrained (*self-w2v*)
- GloVe
  - The smallest Stanford pre-trained model: glove.6b (*stanford-glove*)
  - Self-pretrained (*self-glove*)
- Random
  - Uniformly random initialize embedding weights (*rand*)

Others: ELMO, InferSent, USE

Models

- CNN
    - Embedding layer
    - 3 CNN layers
    - 1 fully connected layer + softmax
- RNN
    - Embedding layer
    - 128 hidden cells
        - Vanilla
        - LSTM
    - 1 fully connected layer + softmax
- FastText (*FT*)
    - 1 fully connected layer + softmax

Training options

- Transfer and freeze embedding
- Transfer and finetune embedding
- Finetune everything else

- Adam optimizer
- Cross-entropy loss
- Batch size: 32 (smaller seems better)

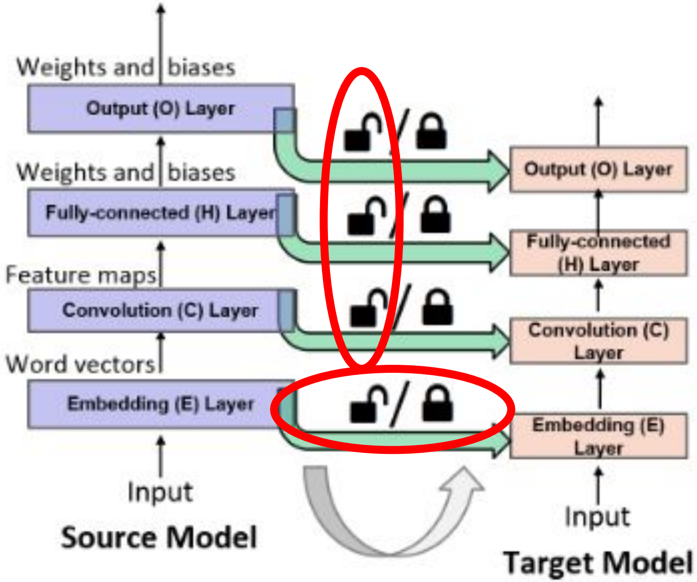
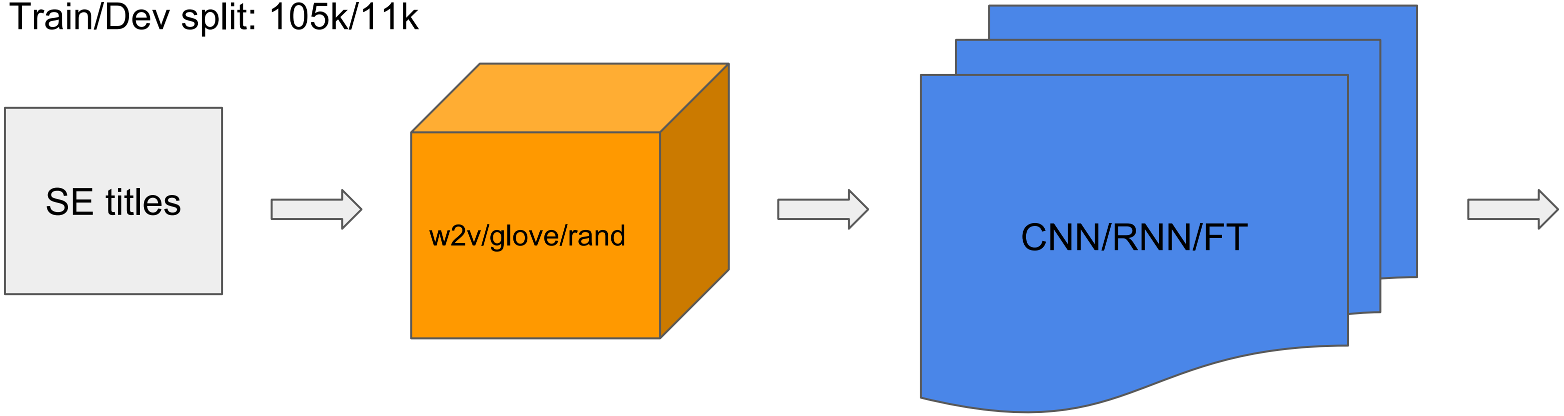


Figure from: [A Practitioners' Guide to Transfer Learning for Text Classification using Convolutional Neural Networks]

Step 0: build a baseline classifier

Vocabulary Size: 37056
Train/Dev split: 105k/11k



id	**title**	content	tag
1	How important is the minimum layer height on a 3d printer?	...	quality, resolution

More details in bitbucket: https://bitbucket.org/rbcmllab/nlp-transfer/src/master/Milestone%20%231%20(Jun19-Jul10).md

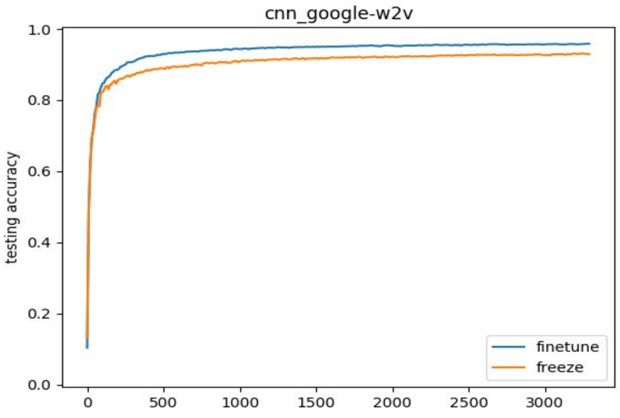
Step 0: build a baseline classifier

- How does each component affect learning
  - Freeze vs. finetune?
  - Embedding methods?
  - Model architectures?

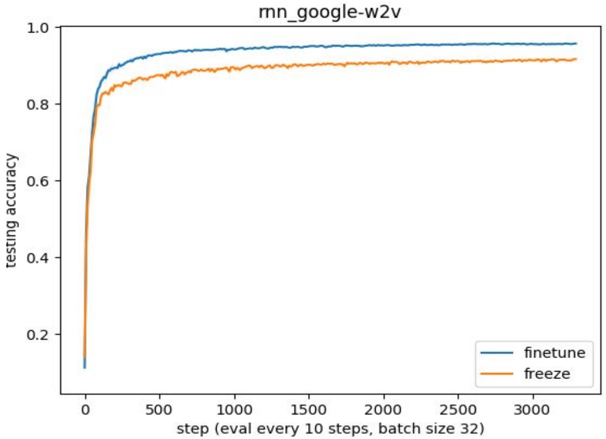
More details in bitbucket: https://bitbucket.org/rbcmllab/nlp-transfer/src/master/Milestone%20%231%20(Jun19-Jul10).md

How does each component affect learning

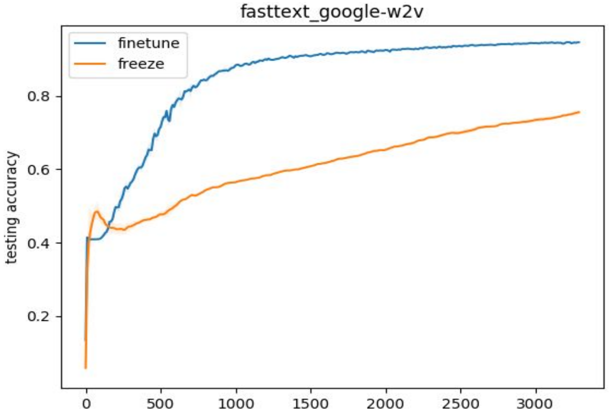
- Freeze vs. **Finetune** (google-w2v embedding)



CNN



RNN-LSTM



FT

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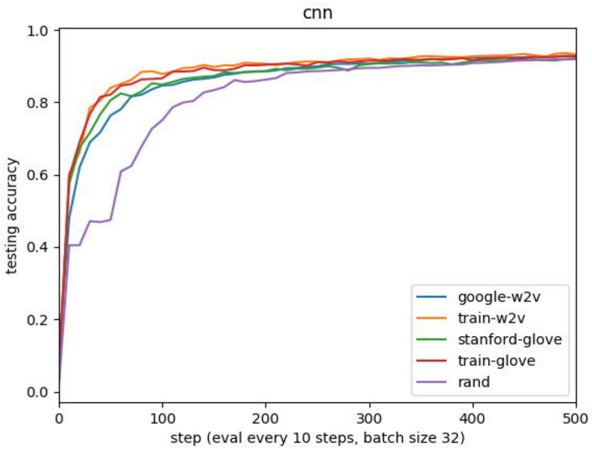
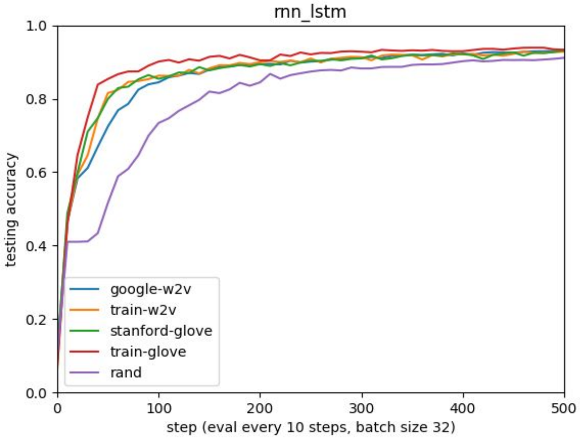
How does each component affect learning

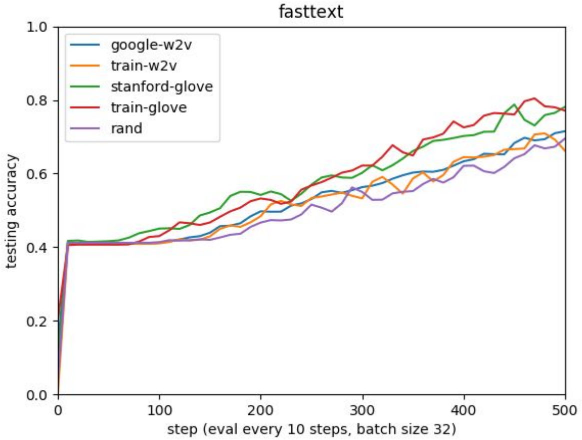
- Which embedding is better?
  - The two “self-train” embeddings seem to be slightly better



CNN



RNN-LSTM



FT

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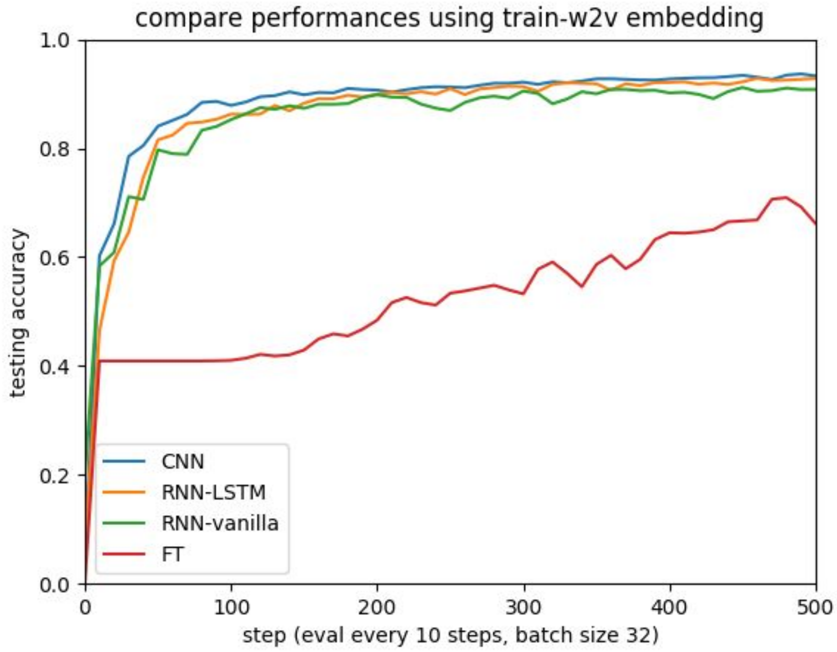
How does each component affect learning

- Which model architecture is better?
  - Compared across models with train-w2v embedding



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Summary on Step 0

- Always finetune the embedding layers
- When your dataset is big enough, self-trained embedding could be better
- CNN seems better in short sentences; consider RNN if sentences are long; one layer model could also achieve comparable results

- What else to try?
  - freeze/finetune other layers
  - Finetune learning rate (Existing framework: ULMFiT)
  - Try larger scale classification

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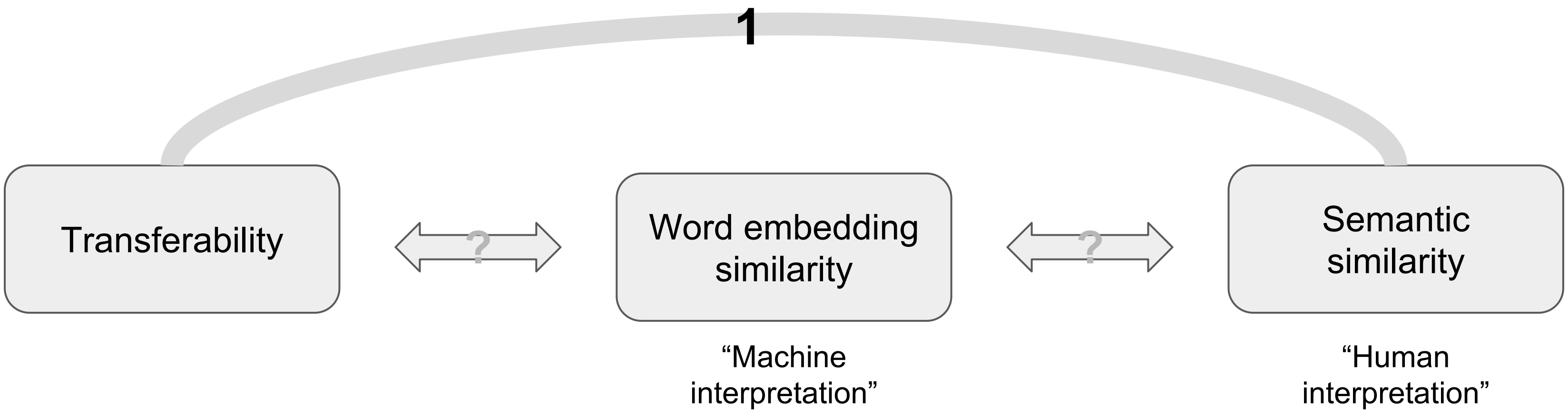
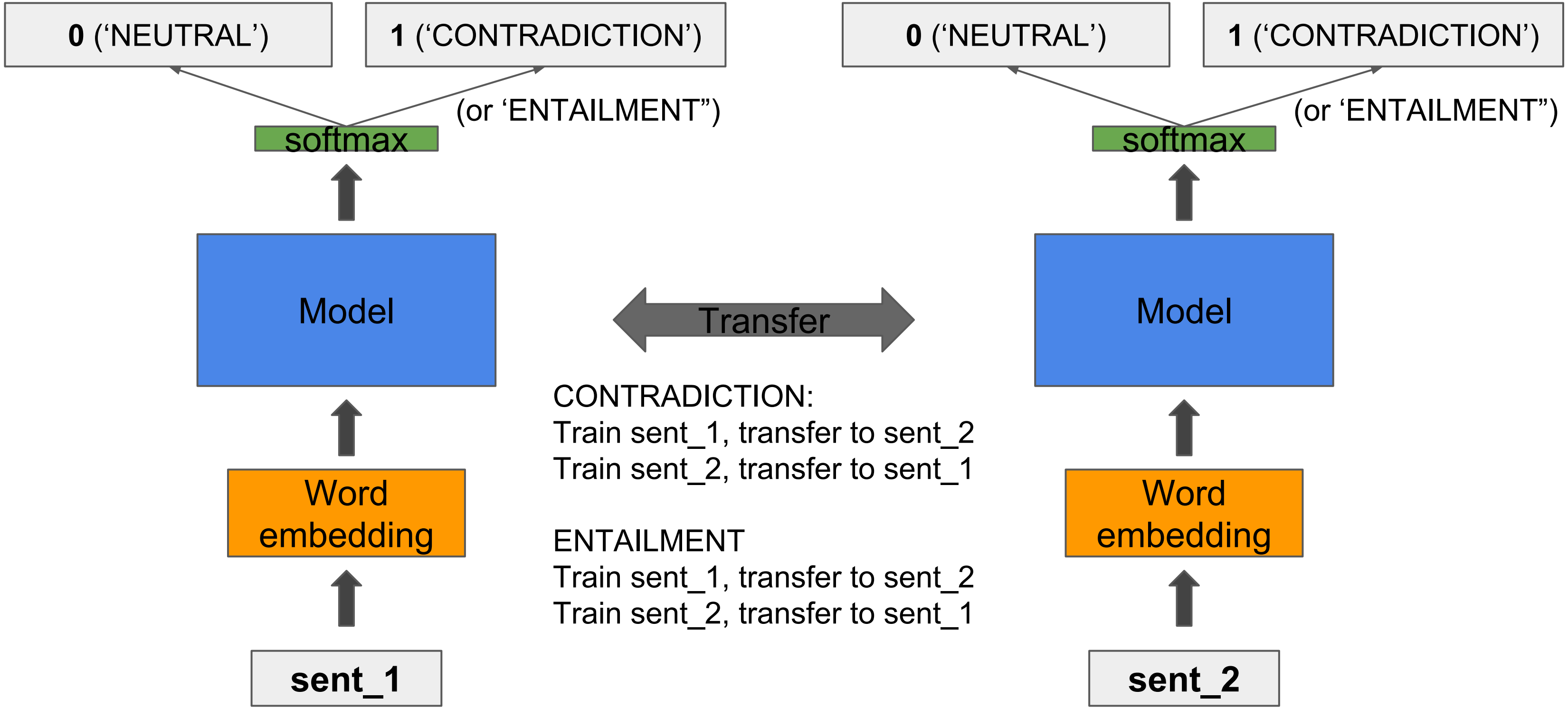
Step 1: transferability ⟷ semantic similarity



SICK data "classification"

id	**sent_1**	**sent_2**	sim	**label**



SICK data "classification"

id	**sent_1**	**sent_2**	sim	**label**

Hypothesis:

"ENTAILMENT" should transfer better than "CONTRADICTION" if we assume that sentences that are "entailed" based on human interpretation means more "similarity"

SICK data “classification”

id	**sent_1**	**sent_2**	sim	**label**

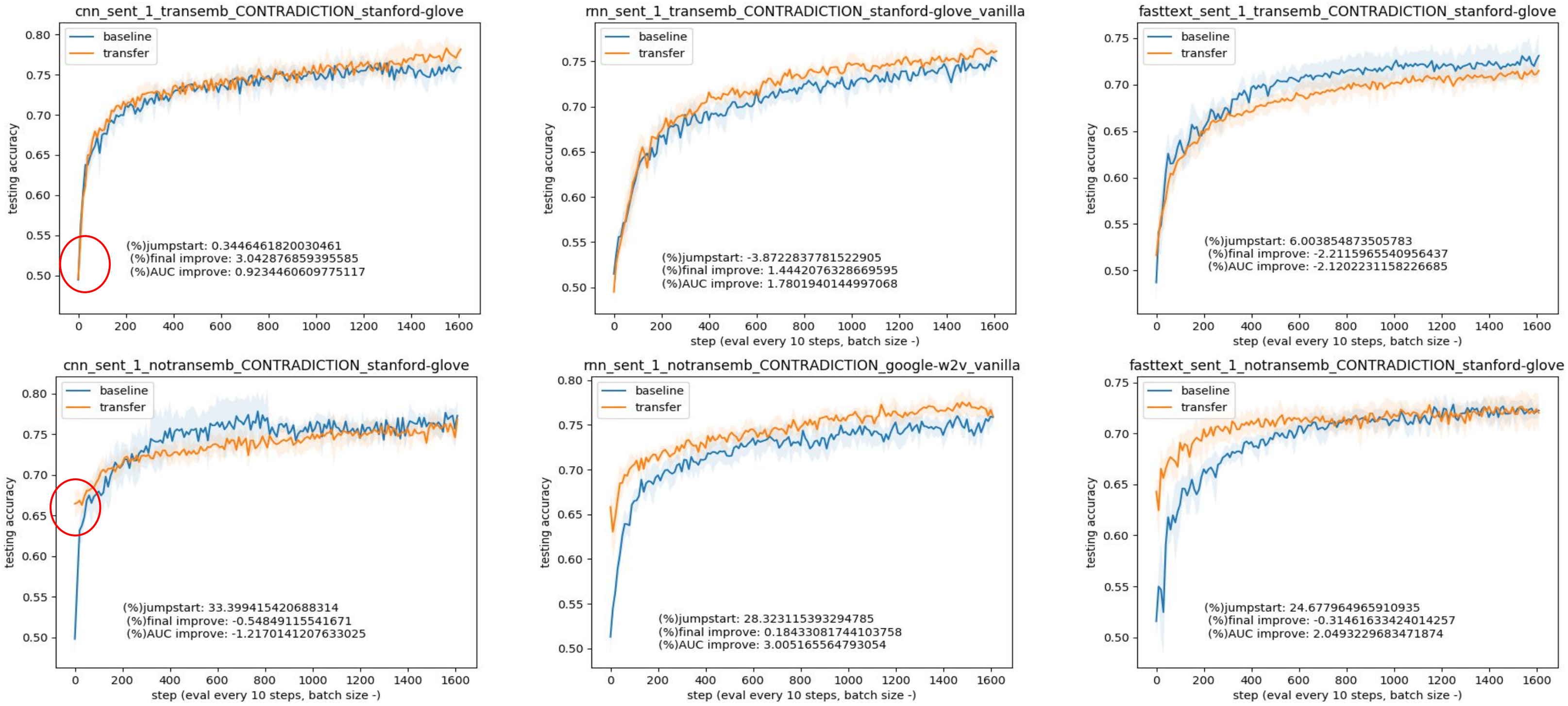
- Evaluate baseline vs. transfer:
  - Jumpstart: accuracy differences at step 0
  - Final improve: accuracy differences at the last step
  - AUC (area under the curve) improve: accumulated accuracy differences

SICK data “classification”: observations

- Do not transfer the embedding layer (stanford-glove, CONTRADICTION)

Transfer emb

Not Transfer emb

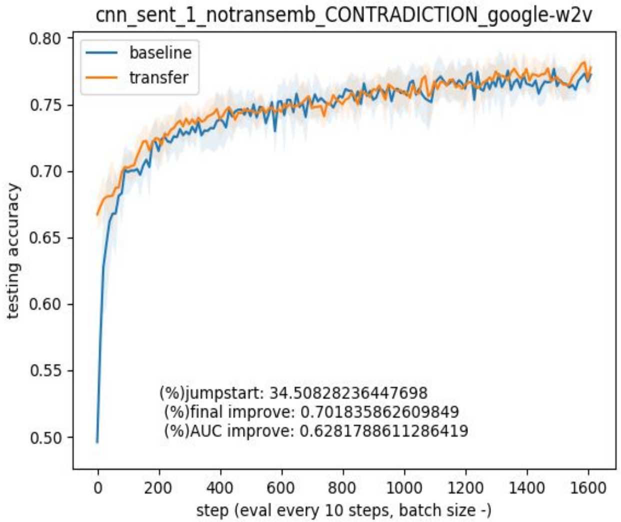


CNN RNN-vanilla FT

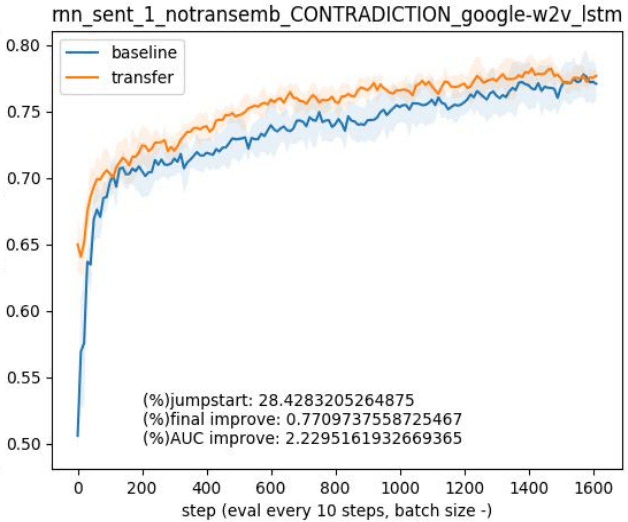
SICK data “classification”: observations

- Distinct behaviours among models;

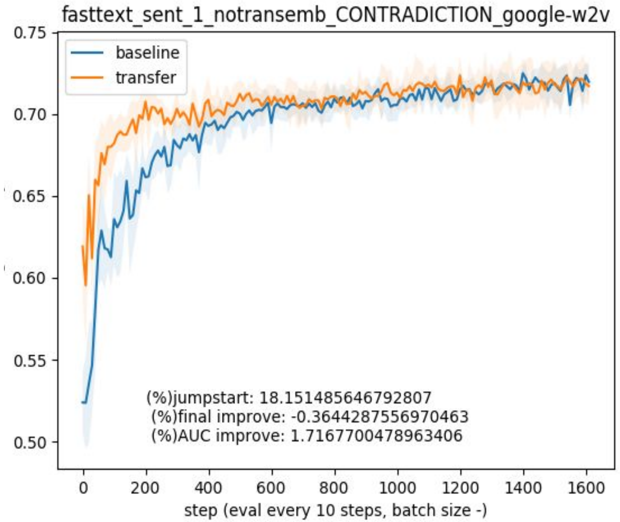
(google-w2v, CONTRADICTION)



CNN



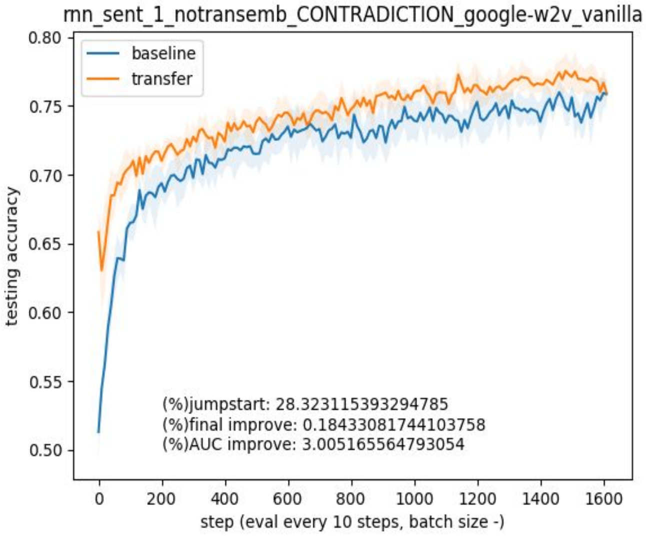
RNN-LSTM



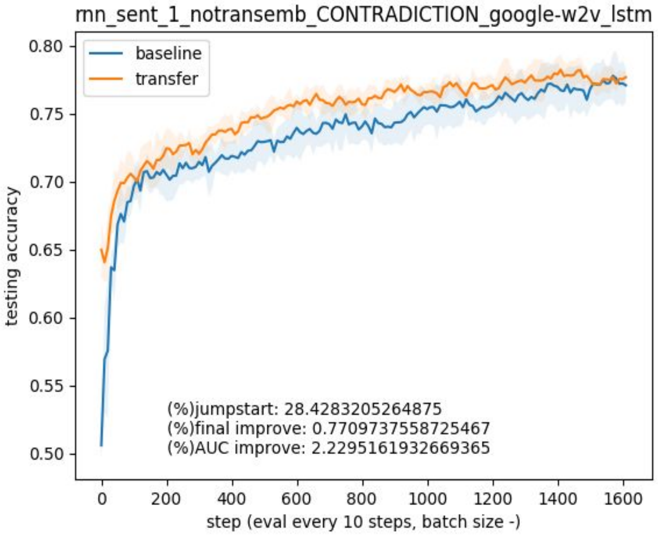
FT

SICK data "classification": observations

- Distinct behaviours among models; while RNN seems to be the most suitable for this transfer task. (google-w2v, CONTRADICTION)



RNN-vanilla



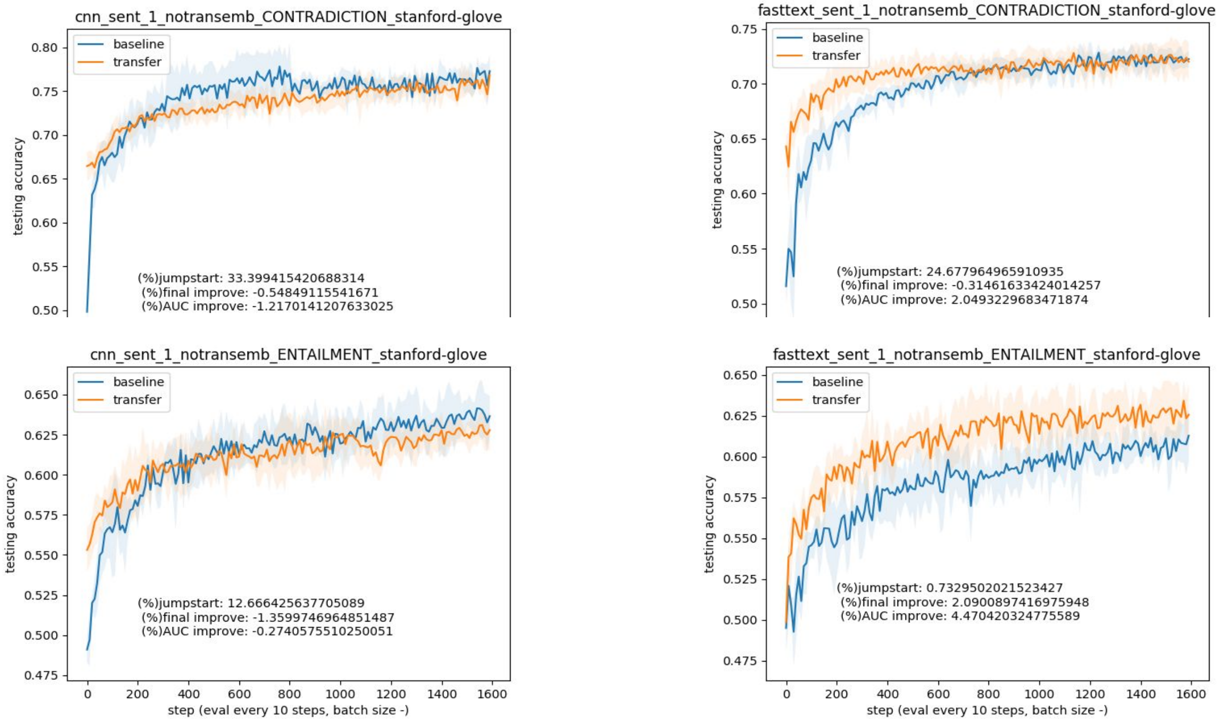
RNN-LSTM

SICK data “classification”: observations

- Overall, “CONTRADICTION” transfers slightly better than “ENTAILMENT”;
- In a few runs “ENTAILMENT” performed well (stanford-glove)

CONTRA

ENTAIL



CNN FT

SICK data “classification”: observations

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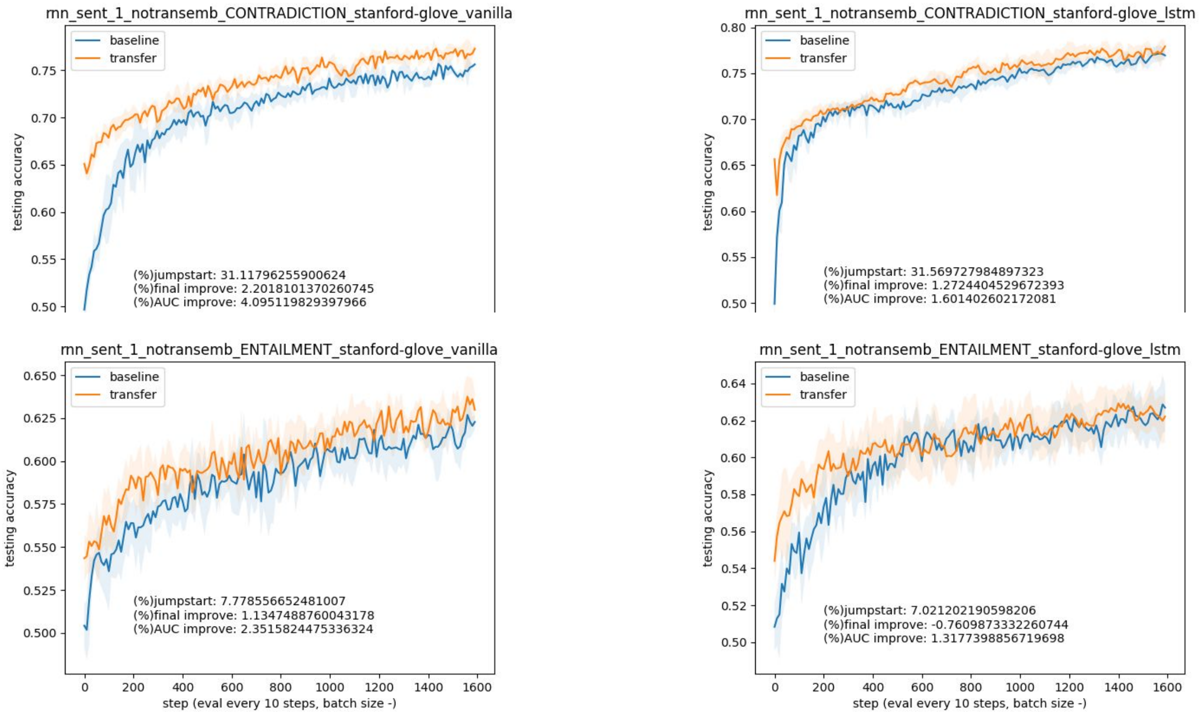
CONTRA

ENTAIL



RNN-vanilla RNN-LSTM

SICK data “classification”

id	**sent_1**	**sent_2**	sim	**label**

Hypothesis:

“ENTAILMENT” should transfer better than “CONTRADICTION” if we assume that sentences that are “entailed” based on human interpretation means more “similarity”

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id	**sent_1**	**sent_2**	sim	**label**

Hypothesis:

"ENTAILMENT" should transfer better than "CONTRADICTION" if we assume that sentences that are "entailed" based on human interpretation means more "similarity"

However…

ENTAILMENT

- *If A is true, then B is true*:
  - A: A dog is running in a field
  - B: An animal is running in a field

NETURAL

- *If A is true, then B cannot be said to be true or false*:
  - A: A man is breaking three eggs in a bowl
  - B: A girl is pouring some milk in a bowl

CONTRADICTION

- *If A is true, then B is false*:
  - A: A man is playing golf
  - B: No man is playing golf

Lesson learned in Step 1

- Experiments were not-so-appropriately designed due to a misunderstanding in the dataset --- understand your data is important

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- Experiments were not-so-appropriately designed due to a misunderstanding in the dataset --- understand your data is important
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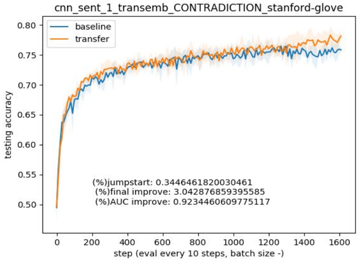
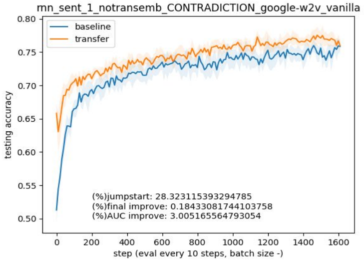
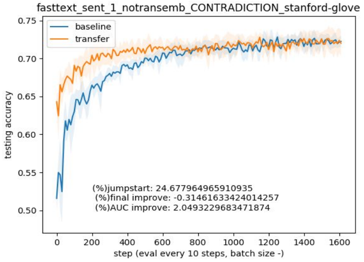
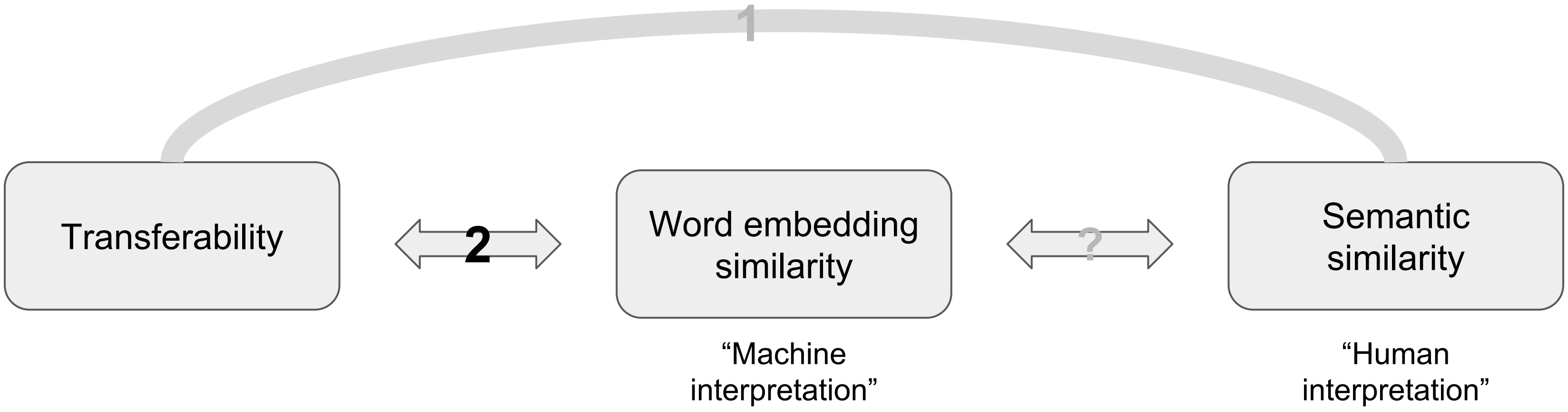
- But...still observed transfer patterns in different model/embedding methods.



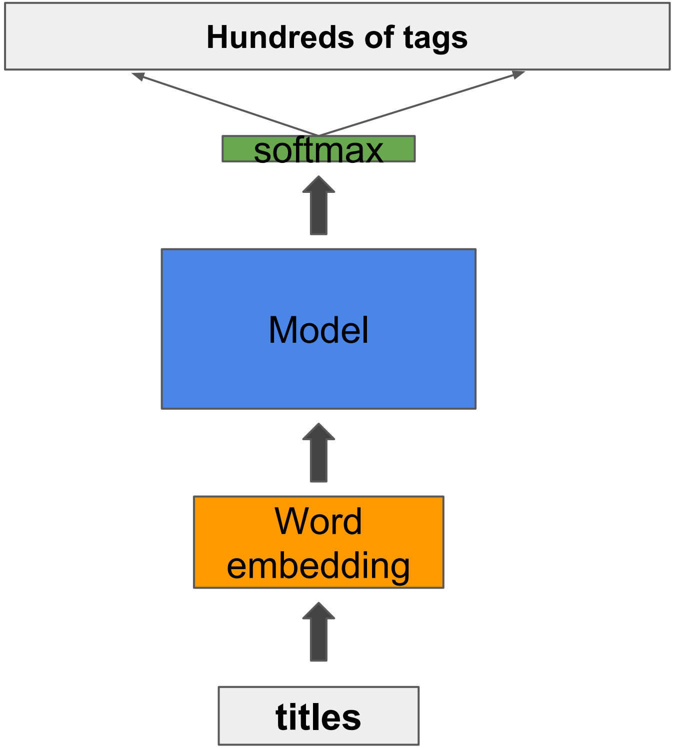




Step 2: transferability ⟷ embedding similarity



Going back to SE data



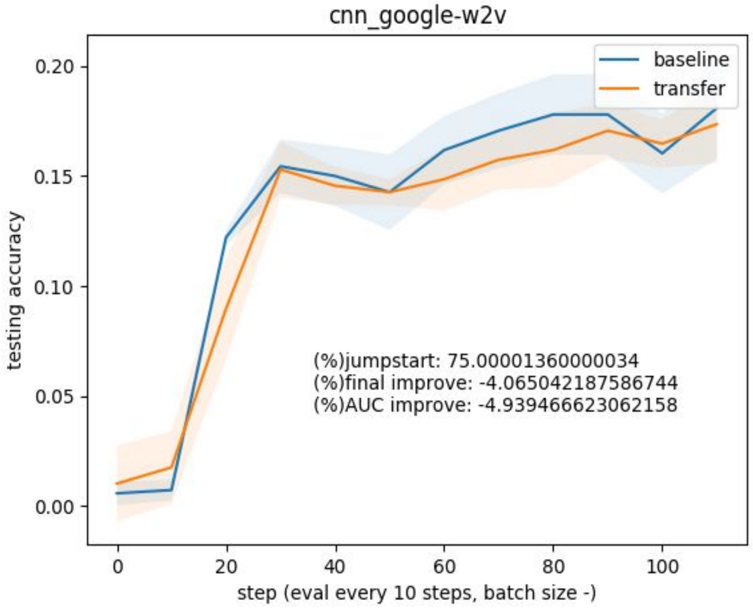
id	**title**	content	**tag**
1	What is the right approach to write the spin controller for a soccer robot?	...	soccer control

- Source: biology, cooking, crypto, diy, robotics, travel
  - Vocabulary Size: 33398
  - Train/Dev split: 78300/8700
  - #tags: 4268
- Target: bioinformatics
  - Vocabulary Size: 2705
  - Train/Dev split: 1228/136
  - #tags: 379

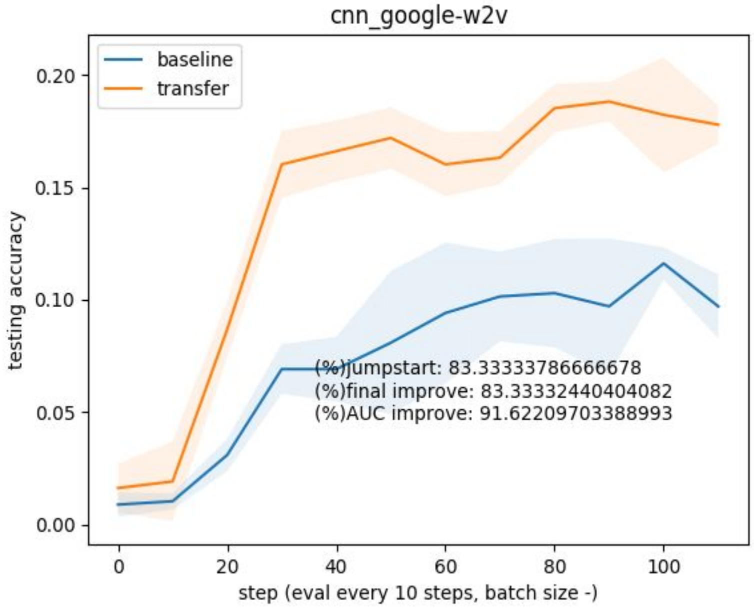
1. Perform transfer
2. Compute embedding distances
3. Is transferability correlated with embedding distances?

Transfer Results

- All sources to “bioinformatics” vs. “biology” to “bioinformatics”
  - CNN model with google-w2v embedding



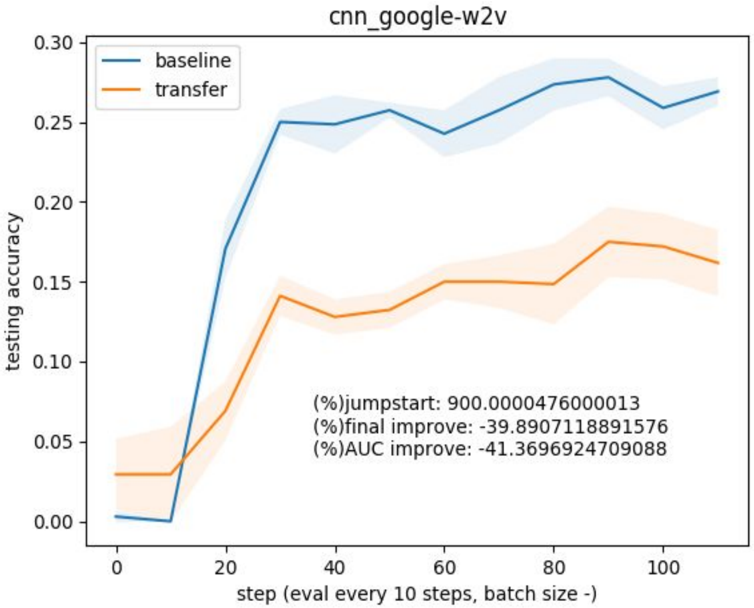
All to “bioinformatics”



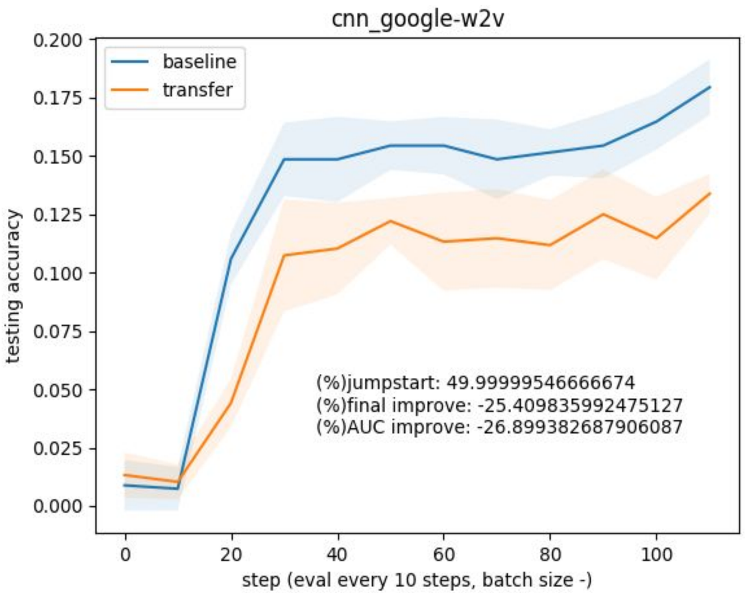
“biology” to “bioinformatics”

Transfer Results

- "diy" to "bioinformatics" vs. "robotics" to "bioinformatics"
  - CNN model with google-w2v embedding



"diy" to "bioinformatics"

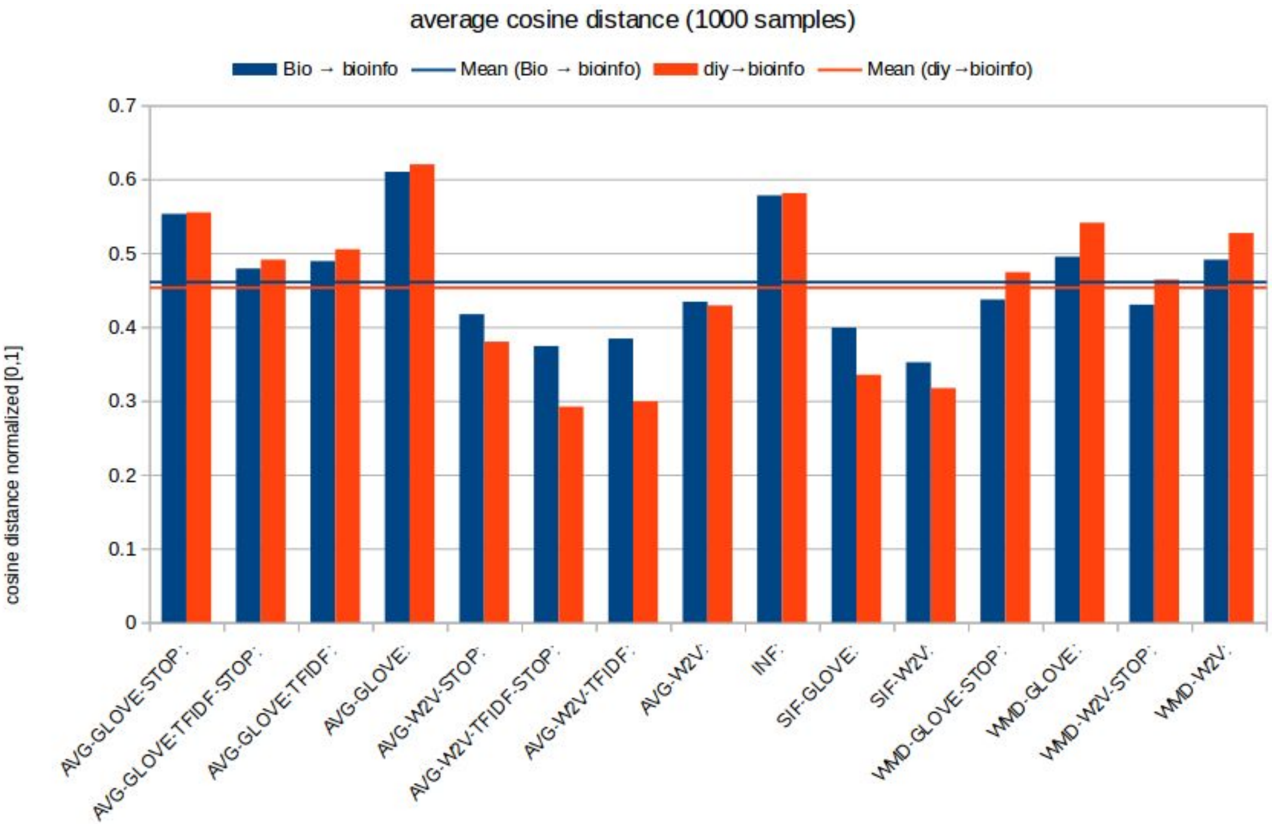


"robotics" to "bioinformatics"

Look at embedding distances

- *m* to *n* pairwise comparison on cosine similarity over the entire source and target sentences, then take the average score (normalized to [0, 1])
    - To save time, we do random sample of 1000 sentences from source and target and average over 5 iterations. (1000 x 1000 x 5 comparisons)
    - Score -> 0: near; Score -> 1: far

Look at embedding distances



Biology -> Bioinformatics: avg 0.46

Diy -> Bioinformatics: avg 0.45

Revisit SICK data

- Is “CONTRADICTION” actually closer in embedding distance? Does that explain why its transfer performed better than “ENTAILMENT”?

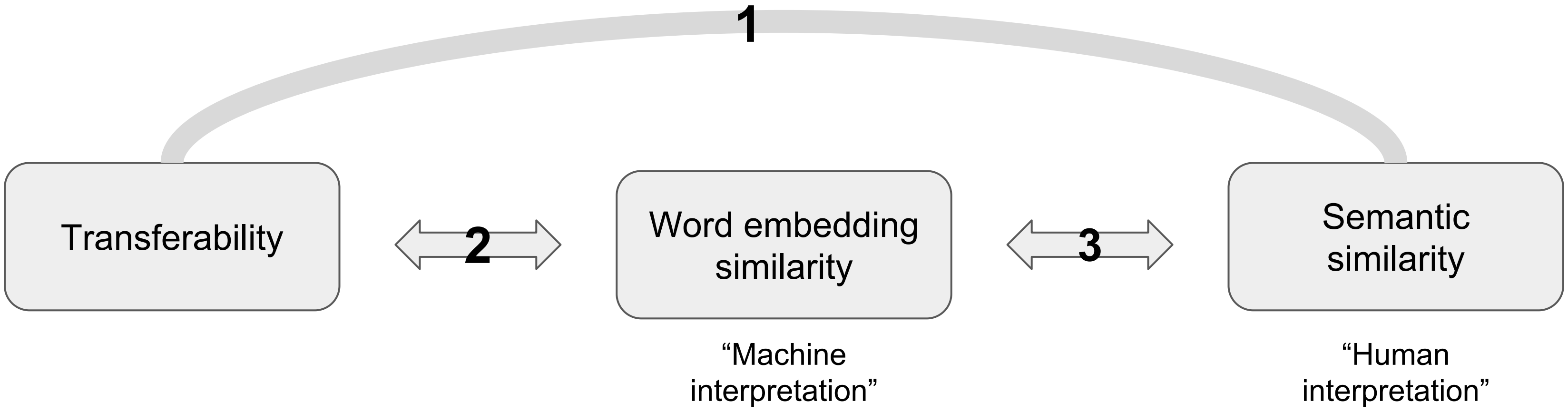
Revisit SICK data

- Is "CONTRADICTION" actually closer in embedding distance? Does that explain why its transfer performed better than "ENTAILMENT"?
- Based on 1 measurement using USE, CONTRADICTION and ENTAILMENT shows the same embedding distance of 0.3

sent_1	**sent_2**	**label**
...	**...**	ENTAILMENT

sent_1	**sent_2**	**label**
...	**...**	CONTRADICTION

Step 3: embedding ⟷ semantic similarity



An existing recent work: [Evaluation of sentence embeddings in downstream and linguistic probing tasks]

Takeaway

- Always finetune a pretrained model with your data (at least in the embedding)
    - But do not transfer the embedding layer
    - If your data is big enough, consider training an embedding from scratch
- Model/embedding selection is still task-dependent
- There are some patterns in transferability vs. “similarity”, but
    - One will need to define a similarity measurement accordingly, multiple measurements should be evaluated
    - In this work we looked at “semantic similarity” as a measurement for transferability, but no solid conclusion on the correlation

Thank you!

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