The Unreasonable Effectiveness of Transfer Learning on NLP

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Strata
DATA CONFERENCE

Bio

- **Research**
  - Urban Mobility | Social Media
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Overview

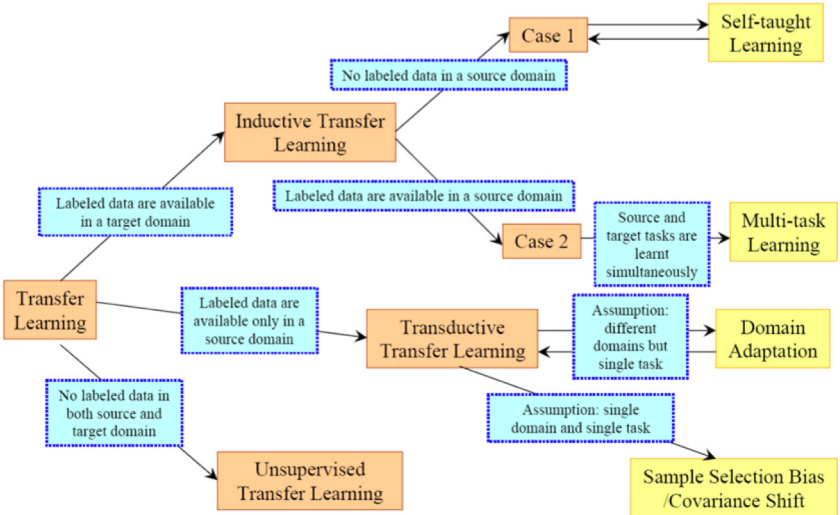
- Transfer Learning
- ImageNet and Feature Hierarchy
- Approaches and Considerations
- Previous attempts in NLP
- Recent advancements
- Language Modeling
- ULMFiT: Universal Language Model for Fine-Tuning
- Code Walkthrough
- Resources

What is Transfer Learning?

- Transfer learning is a concept where we try to leverage knowledge learned previously to solve new problems.
- For example, learning to play one music instrument can facilitate faster learning of another music instrument.

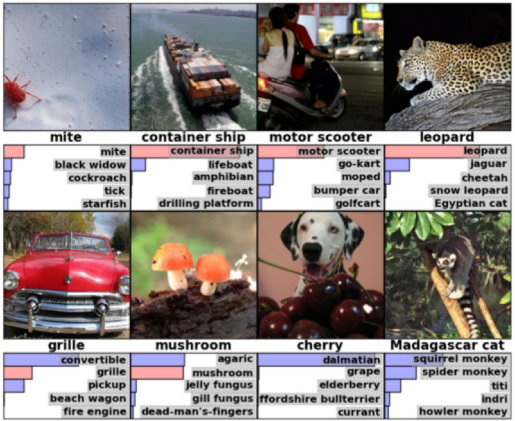
- Transfer learning has gained attention since its discussion in the Neural Information Processing Systems 1995 workshop on ”*Learning to Learn”*.

Overview of Different Settings of Transfer Learning



Source: Pan et al

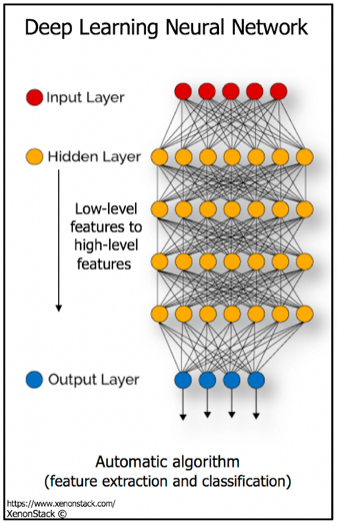
ImageNet Challenge

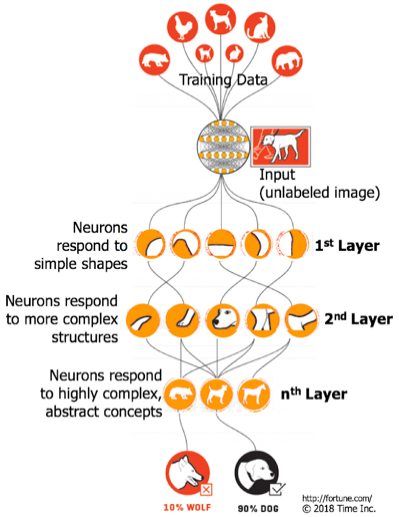


IMAGENET

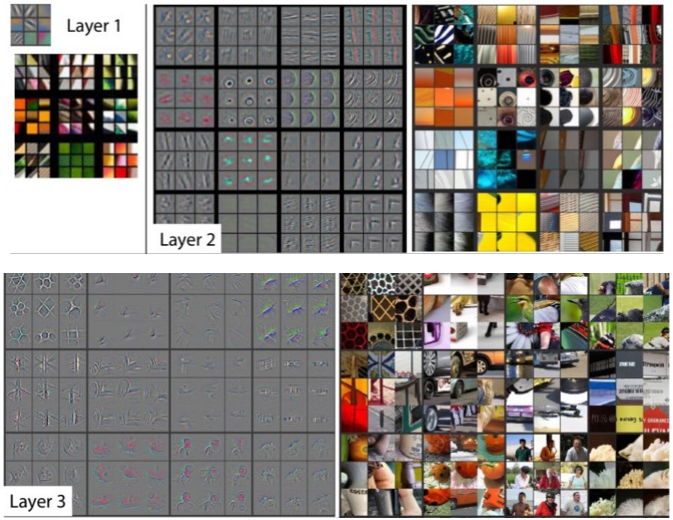
- Published in 2009
- 1.3 million images with 1,000 object classes
- ImageNet Large Scale Visual Recognition Challenge (2010 to 2017)
- AlexNet in 2012, 41% better than 2nd place.
- The beginning of Deep Learning era

Deep Neural Network

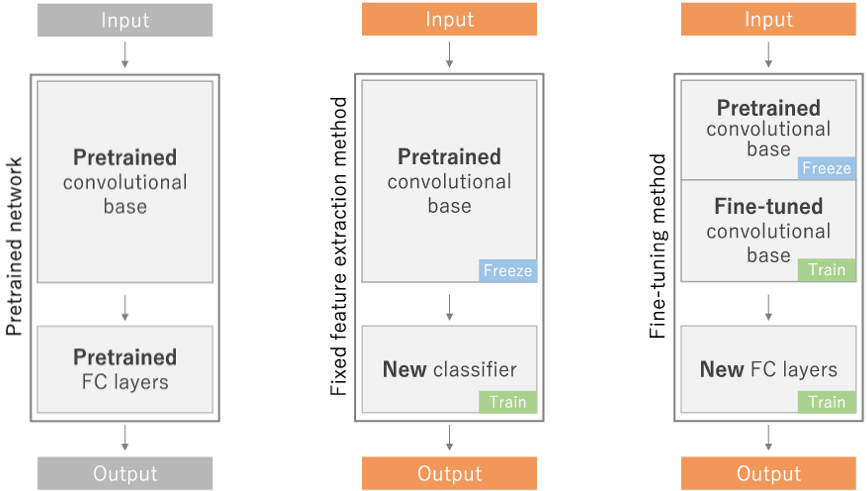




Features learned in each layer

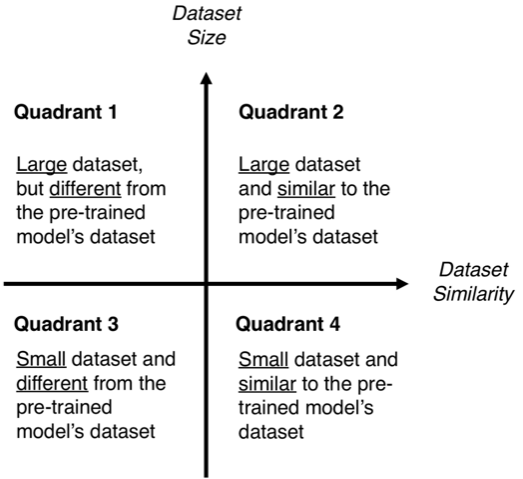


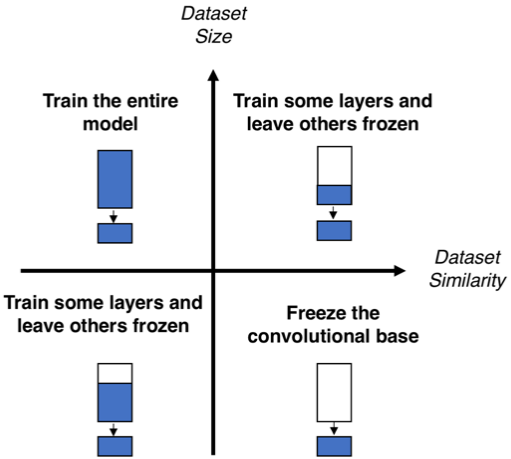
Transfer Learning Approaches



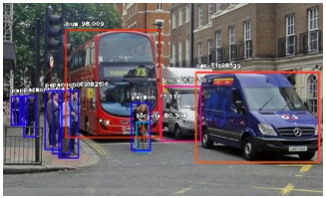
Source: Yamashita et al 2018

Fine-tuning Considerations





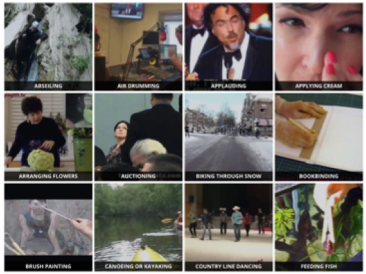
How well do pre-trained ImageNet models generalize?



Object Detection

Human Pose Estimation

Semantic Segmentation



Human Action Classification

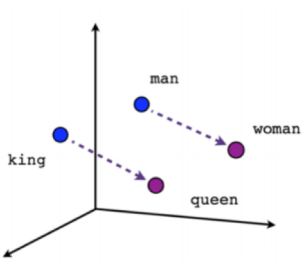
From Computer Vision to NLP

- *Is there a ImageNet-like dataset for natural language?*
  - **Data size**
    - On the order of millions of training examples.
  - **Representative of the problem space**
    - Allows us to learn most of the knowledge / relations required for understanding natural language
  - **Annotations**
    - Good quality labels

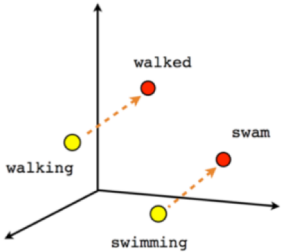
Earlier attempts of Transfer Learning on NLP

- Word embedding models
  - Word2vec (Mikolov et al 2013)
    - Based on distributional hypothesis: Words with similar meanings tend to occur in similar context.
  - GloVe: Global Vectors for Word Representation (Pennington et al 2014)
    - Word co-occurrence count-based approach

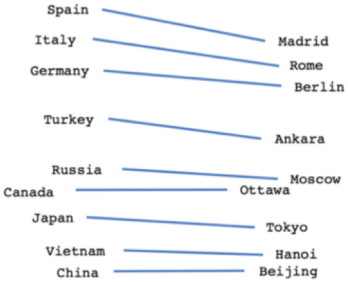
Word Embeddings



Male-Female



Verb tense



Country-Capital

- These embeddings have proven to be efficient in capturing context similarity and analogies
- They are fast and efficient due to its smaller dimensionality

Shortcomings of shallow pre-training I

-0.34	-0.84	0.20	-0.26	-0.12	0.23	1.04	-0.16	0.31	0.06	0.30	0.33	-1.17	-0.30	0.03	0.09	0.35	-0.28	-(

The GloVe word embedding of the word "stick" - a vector of 200 floats (rounded to two decimals).

Source: jalammar.github.io

stick [2] [stik] SHOW IPA

verb (used with object), **stuck, stick·ing.**

1 to pierce or puncture with something pointed, as a pin, dagger, or spear; stab:
to stick one's finger with a needle.

2 to kill by this means:
to stick a pig.

SEE MORE

verb (used without object), **stuck, stick·ing.**

21 to have the point piercing or embedded in something:
The arrow stuck in the tree.

22 to remain attached by adhesion.

SEE MORE

noun

31 a thrust with a pointed instrument; stab.

32 a stoppage or standstill.

SEE MORE

Verb Phrases

36 **stick around** , *Informal* . to wait in the vicinity; linger:
If you had stuck around, you'd have seen the fireworks.

37 **stick by/to**, to maintain one's attachment or loyalty to; remain faithful to:
They vowed to stick by one another no matter what happened.

Source: Dictionary.com

Shortcomings of shallow pre-training II

- Word2vec, GloVe and related methods are *shallow* approaches that trade expressivity for efficiency.
- Using word embeddings is like initializing a computer vision model with pretrained representations that only encode edges, missing the higher-level information required for downstream tasks.
- A model initialized with word embeddings needs to learn from scratch not only to disambiguate words, but also to model complex language phenomena such as long-term dependencies, agreement, negation, and many more.
- Hence, NLP models initialized with these shallow representations still require a huge number of examples to achieve good performance.

Recent Breakthroughs in NLP

- ELMo (Peters et al 2018)
  - “Deep contextualized word representations”
- ULMFiT (Howard et al 2018)
  - “Universal Language Model Fine-tuning for Text Classification”
- OpenAI Transformer (Radford et al 2018)
  - “Improving Language Understanding by Generative Pre-Training”
  - 12 layers, 8 GPUs, 1 month
- BERT (Devlin et al 2018)
  - “BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding”
  - 24 layers, 64 TPUs, 4 days. (8 GPUs, 40 - 70 days)

Common Theme: Language Model

- What is a language model?
  - Generally, a Language Model is a model which is able to predict the next word, based on the sequence of words already seen.
- Language modeling is chosen as the pre-training objective as it is widely considered to incorporate multiple traits of natural language understanding and generation.
- A good language model requires learning complex characteristics of language involving syntactical properties and also semantical coherence.
  - Example: “The service was poor, but the food was _____”
    - Ability to associate attributes used to describe food.
    - Ability to identify that the conjunction “but” introduces a contrast.
- Training of a language model **does not require** any **manual labeling** and is considered as **unsupervised** / **weakly-supervised.**

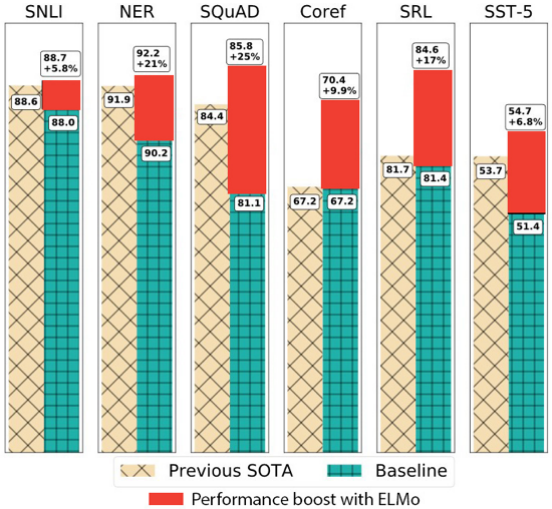
ELMo: Contextualized Word Embeddings

- ELMo (Embeddings from Language Models)
- Instead of using a fixed embedding for each word, ELMo looks at the entire sentence before assigning each word in it an embedding. It uses a bi-directional LSTM trained on a specific task to be able to create those embeddings.

Source: jalammar.github.io

"Deep contextualized word representations" by Peters et al 2018

Achieve SOTA Performance across 6 challenging tasks



- Textual Entailment
- Named Entity Recognition
- Question Answering
- Coreference Resolution
- Semantic Role Labeling
- Sentiment Classification

ULMFiT: Universal Language Model for Fine-Tuning

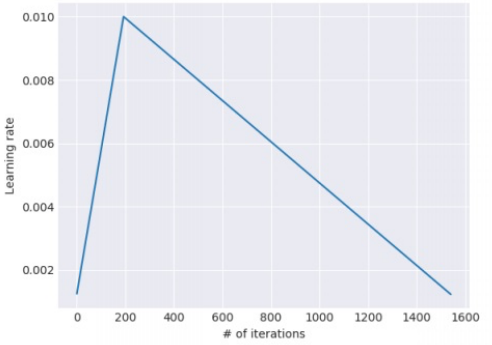
- Proposed by Jeremy Howard and Sebastian Ruder in 2018 as a way to go a step further in transfer learning for NLP.
- The idea is to use a pre-trained language model (on a very large corpus of text, eg: a Wikipedia dump) and use it as a backbone/encoder for any downstream tasks.

3 Stages in ULMFiT

- **General Domain language model pre-training**
  - Language model pre-trained on Wikitext-103 (Merity et al., 2017). It consists of 28,595 pre-processed English Wikipedia articles and 103 million words.
  - AWD-LSTM (“Regularizing and Optimizing LSTM Language Models, Merity et al 2017)
- **Target task language model fine-tuning**
  - Fine-tune the pre-trained language model on data from the target task (on which classification will be performed).
  - The target text has a different distribution than the one on which our language model has been pre-trained.
  - Adjust the model weights such that they adapt to the task-specific text features. This step improves the performance of the downstream application, especially on small datasets.
- **Target task classifier training**

Bag of Tricks I

- Slanted Triangular Learning Rates (STLR)
  - STLR is a modification of the triangular learning rates (Smith et al 2017) with a short increase and a long decay period.
  - Model will quickly converge to a suitable region of the parameter space for the target task. Followed by a long decay period which allows for the further refining of the parameters.



Bag of Tricks II

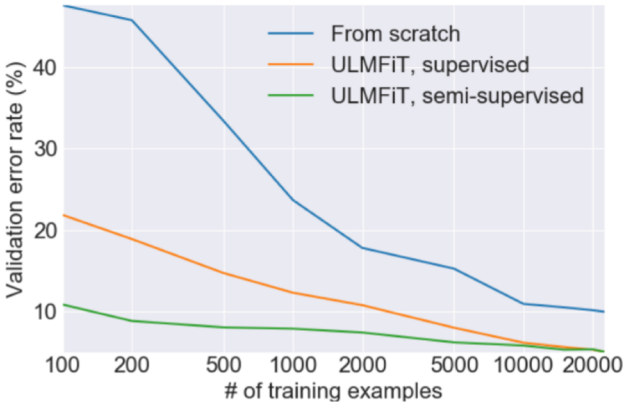
- Discriminative fine-tuning
  - Different layers in a model capture different types of information and hence require different learning rate. The initial layers capture the most general form of information.
  - General information of the language are common and would require the least changes in their weights. The amount of fine-tuning required increases gradually as we move towards the last layer.
  - It first chooses the learning rate of the last layer by fine-tuning only the last layer and uses the following formula for the lower layers
    - $\eta^{l-1} = \eta^{l} * 0.3846$, where η^{l} is the learning rate of the l-th layer.

Bag of Tricks III

- Gradual unfreezing
  - Gradually unfreeze the layers starting from the last layer to prevent catastrophic forgetting
  - When it comes to downstream task (classifier), an aggressive fine-tuning may erase the benefits of language model pre-training.

- How
  - The last LSTM layer is first unfrozen and the model is fine-tuned for one epoch.
  - Then the next lower frozen layer is unfrozen.
  - Repeats for all layers.

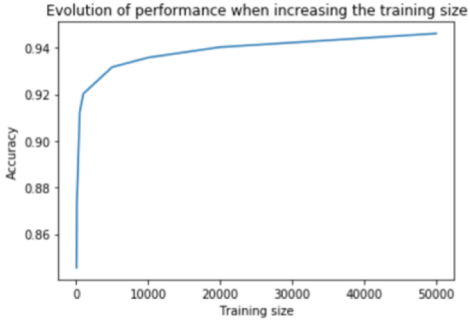
ULMFiT on real-world dataset



- Sentiment classification on IMDB dataset
- With only 100 examples + fine-tuning on pre-trained model, the performance is equivalent to the model trained from scratch with 20,000 examples!

Sentiment Classification on Amazon Review Dataset

- Inspired by the work done by Peter Martigny and his team from Feedly
- Blogpost - https://blog.feedly.com/transfer-learning-in-nlp/
- Results
  - Even with 50 samples only, they achieved 85% accuracy.
- ULMFiT beats the reported score from FastText (~92%) with just 1000 samples.
- Note that the reported score from FastText was using all 3.6M training samples.
- Based on Fastai v0.7 and PyTorch 0.4



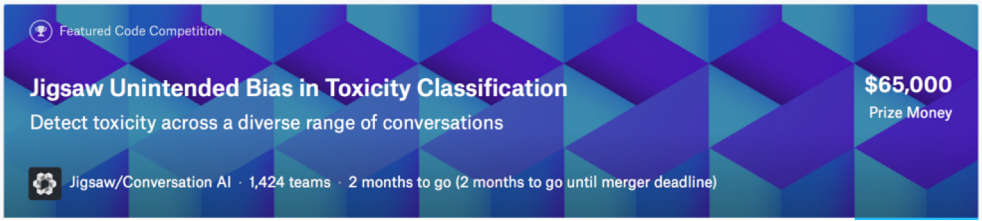
Code Walkthrough

- Sentiment Classification on Amazon Review Dataset
- Ported to Fastai v1 library, compatible with PyTorch v1 and CUDA 10
- Code to be shared on Github: https://github.com/davidlowjw/strata_london_talk_ulmfit

Resources

- “BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding” by Devlin et al 2018
- https://openai.com/blog/better-language-models/ - OpenAI GPT-2
- https://fast.ai - Making neural nets uncool again
- http://ruder.io - Sebastian Ruder’s blog

Practice on a Kaggle competition



- An extension to “Toxic Comment Classification Challenge” last year.
- Build a model that detects toxicity and minimizes unintended bias associated with mentions of certain identities.

Paradigm Shift

- What we have witnessed in 2018
  - Paradigm shift from pre-trained Word Embeddings to Language Models
  - From just initializing the first layer of our models to pretraining the entire model with hierarchical representations.
  - If learning word vectors is like only learning edges, these approaches are like learning the full hierarchy of features, from edges to shapes to high-level semantic concepts.
- Bring us a step closer to Natural Language Understanding
- Looking forward to more exciting developments in the next few years!

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