Conclusion and Future Research Directions
Recent Advances in Transferable Representation Learning (Part IV)

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What has representation learning enabled?

Raw data → Feature Extraction → Domain-specific decision making

Automatic, end-to-end
Why Transferability is Important

- In some domains, we have lots of learning resources.
- In other domains, learning resources are insufficient.
Why Transferability is Important

- Knowledge is interchangeable across different domains.
- Leveraging the knowledge from high-resource domains to help decision making in low-resource domains.
- Making learning and inference generalizable and adaptive.
Conclusion

- Research Questions We Have Discussed

  - **Languages**
    - Can we learn representations of concepts in a way that is independent of the language?
    - Can we use it to perform well in languages with very little annotated data?

  - **Modality**
    - Can we learn representations that capture both visual and textual properties?
    - Can we use it to improve performance on relevant tasks?

  - **Domains**
    - Can we capture the association of knowledge with limited supervision?
    - Can we effectively populate missing knowledge in domains?
Several Perspectives of Future Work

- Transferable representations for highly complex structures
  - Hierarchical structures
  - Order-invariant structures

- Fairness and trustworthiness in knowledge transfer

- The emerging application scenarios requiring transferable representation learning
Transferable hyperbolic representation learning

- Many data form hierarchies
  - Ontologies, taxonomies, syntax trees, org charts, citation graphs, etc.

- Particularly suitable for a **hyperbolic space**
  - The amount of space increases exponentially w.r.t. the radius [Nickel+ NIPS-17, Ganea+ NeurIPS-18, Liu+ NeurIPS-19]

- Transferable hyperbolic representation learning benefits tasks
  - Ontology matching and population
  - Label space transfer for hierarchical classification
  - Transfer learning on programming languages (or ASTs)
Transferable set learning

- Unordered and unsized data (i.e. forming a set)
  - Point cloud
  - Clinical events in single-visit electronic health records (EHR)

- Set learning: order-invariant representation learning
  - Differentiable pooling [Zaheer+ NIPS-17]
  - Permutation neural networks [Meng+ KDD-19]

- Applications
  - Risk prediction on EHR data: given a set of lab tests, predict possible diseases / future clinical events
  - Self-driving: learning from a sensor point cloud to predict driving actions

- Why transferability
  - Clinical data are often low-resource due to privacy
  - Models must be generalizable in clinical and self-driving scenarios
Fairness and Trustworthiness

- **Trustworthiness**: when combining multiple sources of knowledge, which one should we believe when there is inconsistency?

- **Fairness**: how do we mitigating societal bias in different domain/language-specific data?
An Emerging Area: Representation Learning for Genomic Data

An example task: Protein-protein interaction prediction.

*Chen+ ISMB'19, Bioinformatics 2019*
Cross-species Transferability: Why Important

Emerging topic: transferability across species

1.2 billion years of evolution distance

Yeast

Train

X

Predict PPI

Arabidopsis

Train

✗

Predict PPI

Tomato

0.12 billion years of evolution distance

PIP: PIPR [Chen+ ISMB’19]: >97% in F1 scores for PPI prediction.
Cross-species Transferability: What Are Needed?

- **<3.5k “high-resource” species vs 1.5M “low-resource” species**
  - Complex organisms without full genomes
  - Newly discovered ones

- Transferred learning is important for *de novo* prediction on **1.5M “low-resource” species**
  - Reliable *de novo* prediction can be used to guide wet lab experiments

- **New technologies for the community**
  - Adversarial learning for “species-invariant” sequence representations
  - Massively *pre-trained language models* for amino acid sequences
Transferable representation learning could address problems in multiple research areas. There are lots of challenges before making it work for Good.
Thank You