

## Literature review of SOTA Transfer Learning and Multi-task Learning applications

Jiaxi Zhao, 20.04, Guided Research Presentation

sebis

Chair of Software Engineering for Business Information Systems (sebis) Faculty of Informatics Technische Universität München wwwmatthes.in.tum.de



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Goals
Concept
Iodel Structure
asks
<ul> <li>Text</li> </ul>
<ul> <li>Protein</li> </ul>
<ul> <li>Source code</li> </ul>
Conclusion
Outlook

**Motivation** 



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Conclusion	





## ·Analysing TL and MTL application cases.

Summarizing TL and MTL suitable conditions.

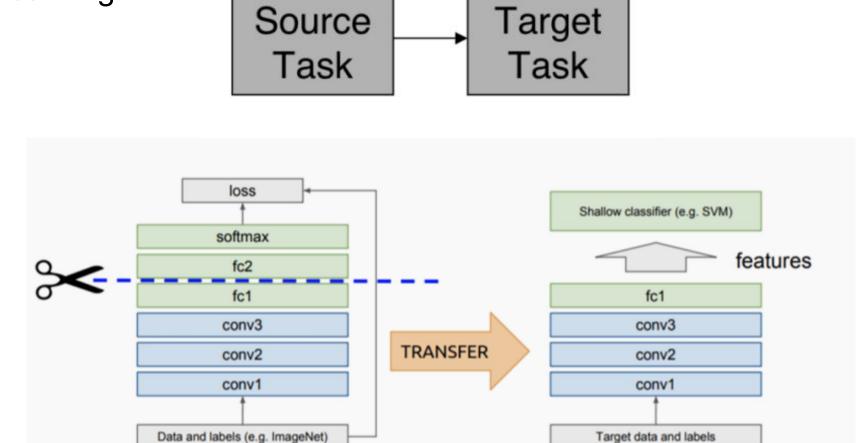
 $\cdot G$ uidance for researchers to solve data scarcity with TL&MTL by writting a 75 pages research paper.



#### Motivation Goals Concept Model Structure Tasks • Text • Protein • Source code

Conclusion

Transfer Learning:



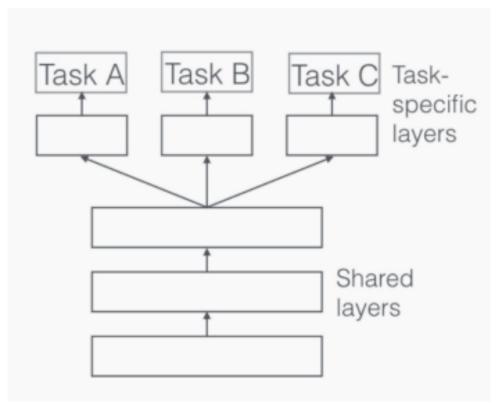
Transfer Learning with Pre-trained Deep Learning Models as Feature Extractors

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#### Concept



Multi-Task Learning:



Concept

## Relation:

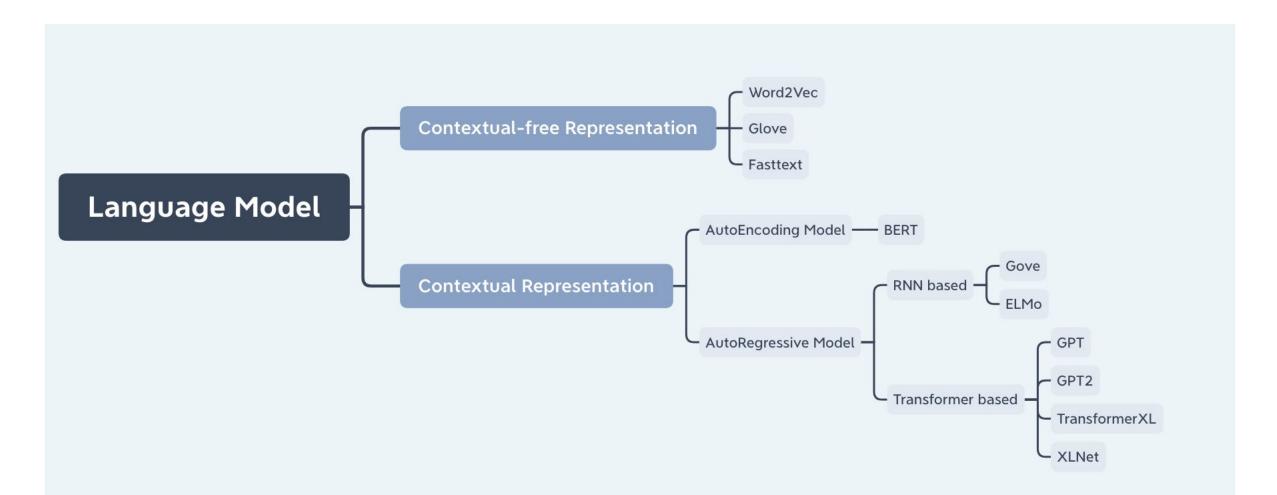
Transfer Learning Settings	Related Areas	Source Domain Labels	Target Domain Labels	Tasks
Inductive Transfer Learning	Multi-task Learning	Available	Available	Regression,
				Classification
	Self-taught Learning	Unavailable	Available	Regression,
				Classification
Transductive Transfer Learning	Domain Adaptation, Sample	Available	Unavailable	Regression,
	Selection Bias, Co-variate Shift			Classification
Unsupervised Transfer Learning		Unavailable	Unavailable	Clustering,
				Dimensionality
				Reduction

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#### Model structure



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#### Model principle



#### **Contexual free models**: Co-occurance Matrix

	C1	C2	C3	C4	C5
W1	1	0	0	2	0
W2	0	4	1	0	0
W3	2	0	0	1	0

AutoEncoding models: Masked tokens

RNN based models: Recurrent Neural Network

Transformer based model:  $P(x) = \prod_{t=1}^{T} p(x_t | x_{< t})$  or  $P(x) = \prod_{t=T}^{1} p(x_t | x_{> t})$ .

#### Comparison Table

	Pros	Cons
Contextual free model	Low computing resource	only allow single context independent representation
AutoRegressive modelRNN	generate context dependent embeddings	Can't encode too long sentences
AutoEncoding model	supports bidirectional context reconstruction	inappropriate assumption: all masked tokens are constructed separately
AutoRegressive modelTransformer	consider sequential relationship between tokens	only encode a uni-directional context

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- Protein
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Conclusion





Task	Transfer Learning	MultiTask Learning	Model
Domain Adaption on Reading Comprehension	YES		BERT
Question Answering Sentence Selection	YES		BERT
Thermal dynamic modeling	YES		LSTM
Negation Detection	YES		BERT
Negation Detection		YES	BiLSTM
Natural language understanding		YES	BERT
Language Translation		YES	LSTM



Task	Transfer Learning	MultiTask Learning	Model
Protein structure prediction	YES		ELMo
Protein structure prediction	YES		Bi-direction Transformer
Protein structure prediction Protein Evolutionary Understanding	YES		LSTM
Protein ontology prediction Remote homology and fold prediction	YES		LSTM
Protein function prediction		YES	Multi-label Deep NN

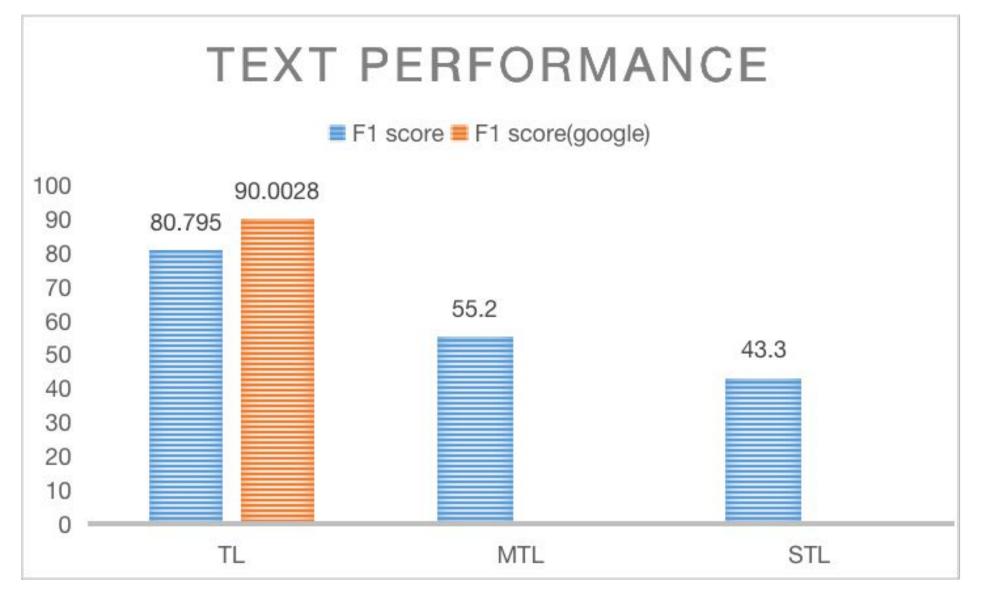
Task	Transfer Learning	MultiTask Learning	Model
Syntax detection	YES		LSTM
Code semantic embedding	YES		LSTM
Code clone detection	YES		RNN
API knowledge summarization Code summarization	YES		RNN
Semantic labeling	YES		CNN

#### **Pros and Cons**

	Transfer Learning	MultiTask Learning
Pros	Make use of previous knowledge, no need to train from scratch. Low computing power	Introduce noisy data, increase generalization
Cons	Need massive pre-training data for generalization	Need to find suitable related tasks. Computing power needed

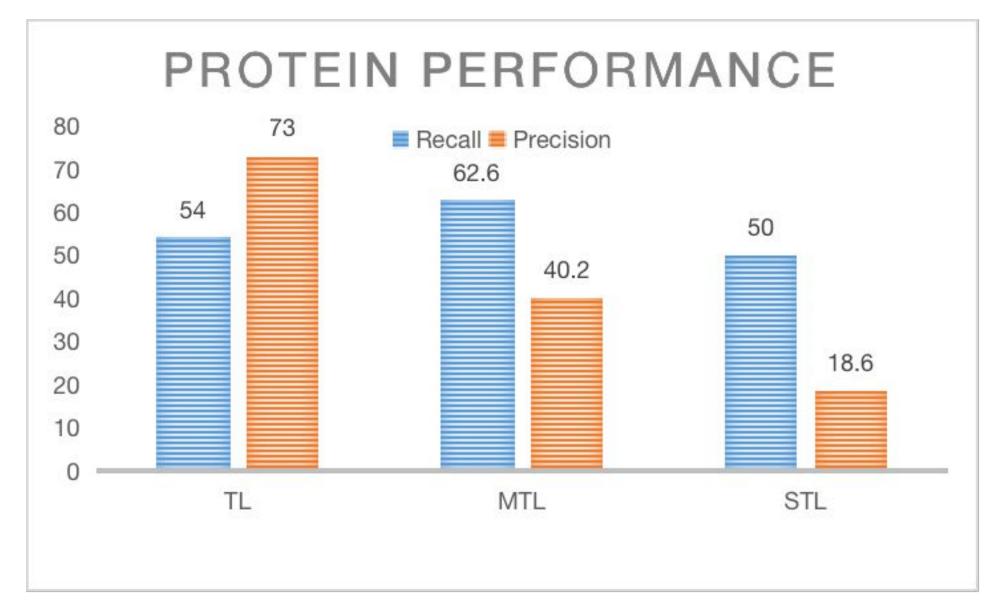
#### Statistics : Text





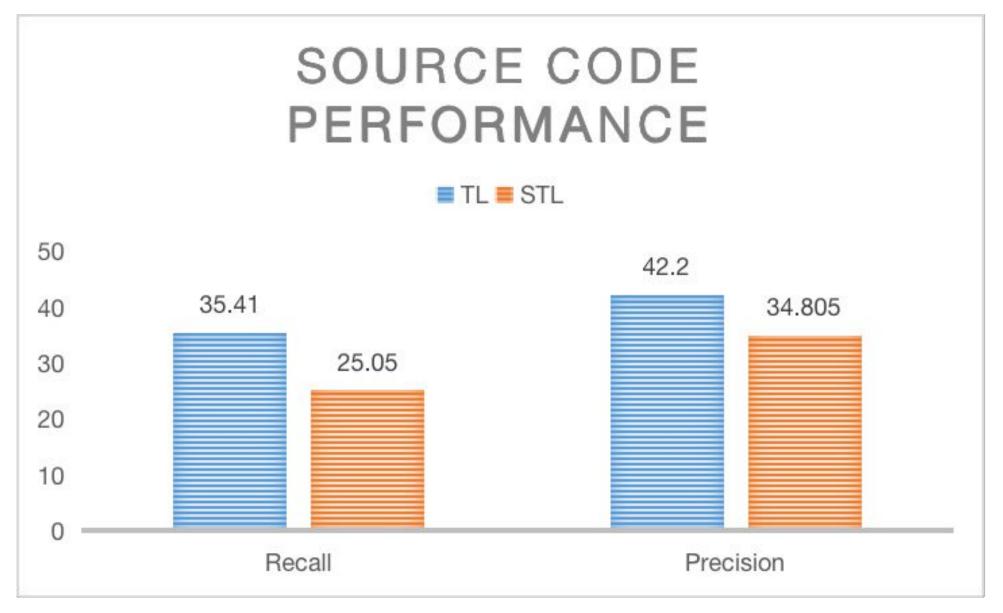
#### Statistics: Protein





#### Statistics: Source code





Goals

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#### Conclusion



Multi-task Learning Related tasks

source:https://cn.dreamstime.com/%E5%85%8D%E7%89%88%E7%A8%8E%E5%BA%93%E5%AD%98%E5%9B%BE%E7%89%87-3d%E5%B0%8F%E6%84%9F%E5%8F%B9%E5%8F%B7%E7%9

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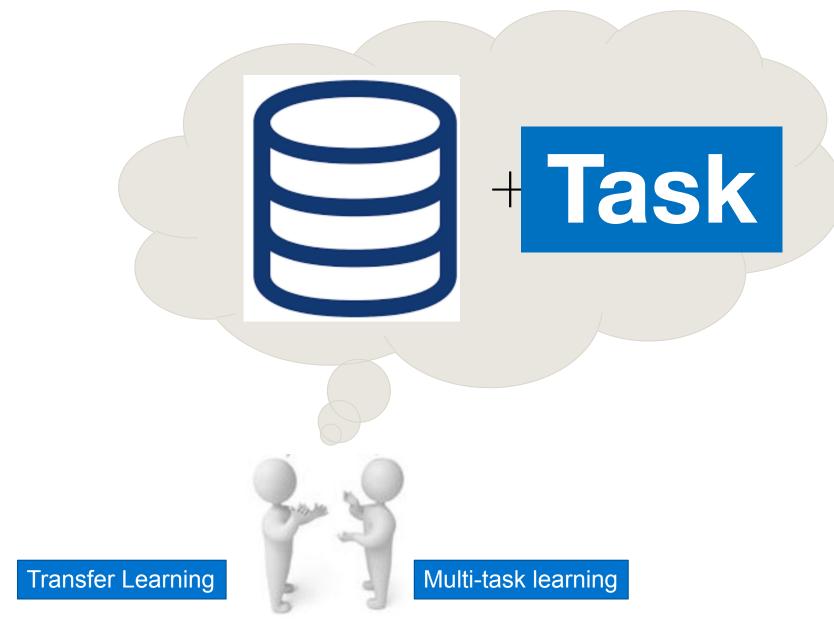
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# Thanks for your attention!

### Appendix1--TEXT

Task	F1	ΜΑΡ	MAPE	Mean accuracy	Glue	Perplexity
Domain Adaption on Reading Comprehension	87.06					
Question Answering Sentence Selection		93.3				
Thermal dynamic modeling			1.396%			
Negation Detection	94.53					
Negation Detection				86.04		
Natural language understanding					93.1	
Language Translation						8.2

#### Appendix2--PROTEIN

Task	Q3	PLOT	Precision	Recall	AUC	F1
Protein structure prediction	70.3					
Protein structure prediction		PLOT				
Protein structure prediction Protein Evolutionary Understanding			73			
Protein ontology prediction Remote homology and fold prediction				54	89	
Protein function prediction			38.9	62.6		48

#### Appendix3--SOURCE CODE

Task	MRR	Accuracy	AUC	Precision	Recall	F-score
Syntax detection	0.52					
Code semantic embedding		88.09				
Code clone detection			82.4			
API knowledge summarization Code summarization				42.2	35.41	37.91
Semantic Labeling	e)		0.769			© sebis 25