Analyzing Neural Language Models Introduction

Shane Steinert-Threlkeld

Mar 30, 2022

Today's Plan

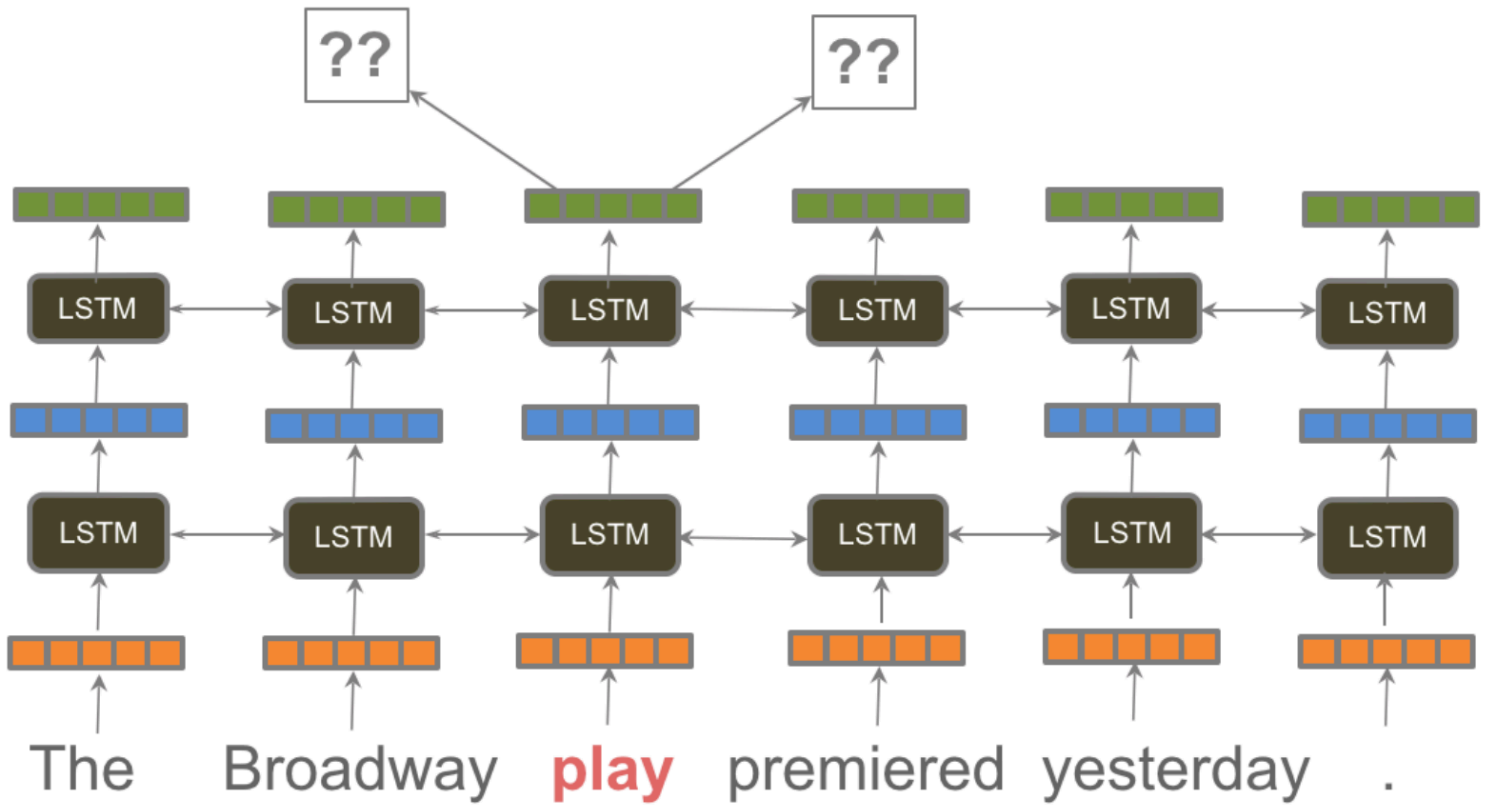
- Motivation / background
  - NLP's "ImageNet moment"
  - NLP's "Clever Hans moment"
- 15 minute break
- Course information / logistics

Motivation

NLP's "ImageNet Moment"

The Gradient

HOME EDITOR'S NOTE OVERVIEWS PERSPECTIVES ABOUT SUBSCRIBE



NLP's ImageNet moment has arrived

08.JUL.2018

[link]

What is ImageNet?

ImageNet: A Large-Scale Hierarchical Image Database

Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li and Li Fei-Fei
Dept. of Computer Science, Princeton University, USA
{jiadeng, wdong, rsocher, jial, li, feifeili}@cs.princeton.edu

Abstract

The explosion of image data on the Internet has the potential to foster more sophisticated and robust models and algorithms to index, retrieve, organize and interact with images and multimedia data. But exactly how such data can be harnessed and organized remains a critical problem. We *content-based image search and image understanding algorithms, as well as for providing critical training and benchmarking data for such algorithms.*

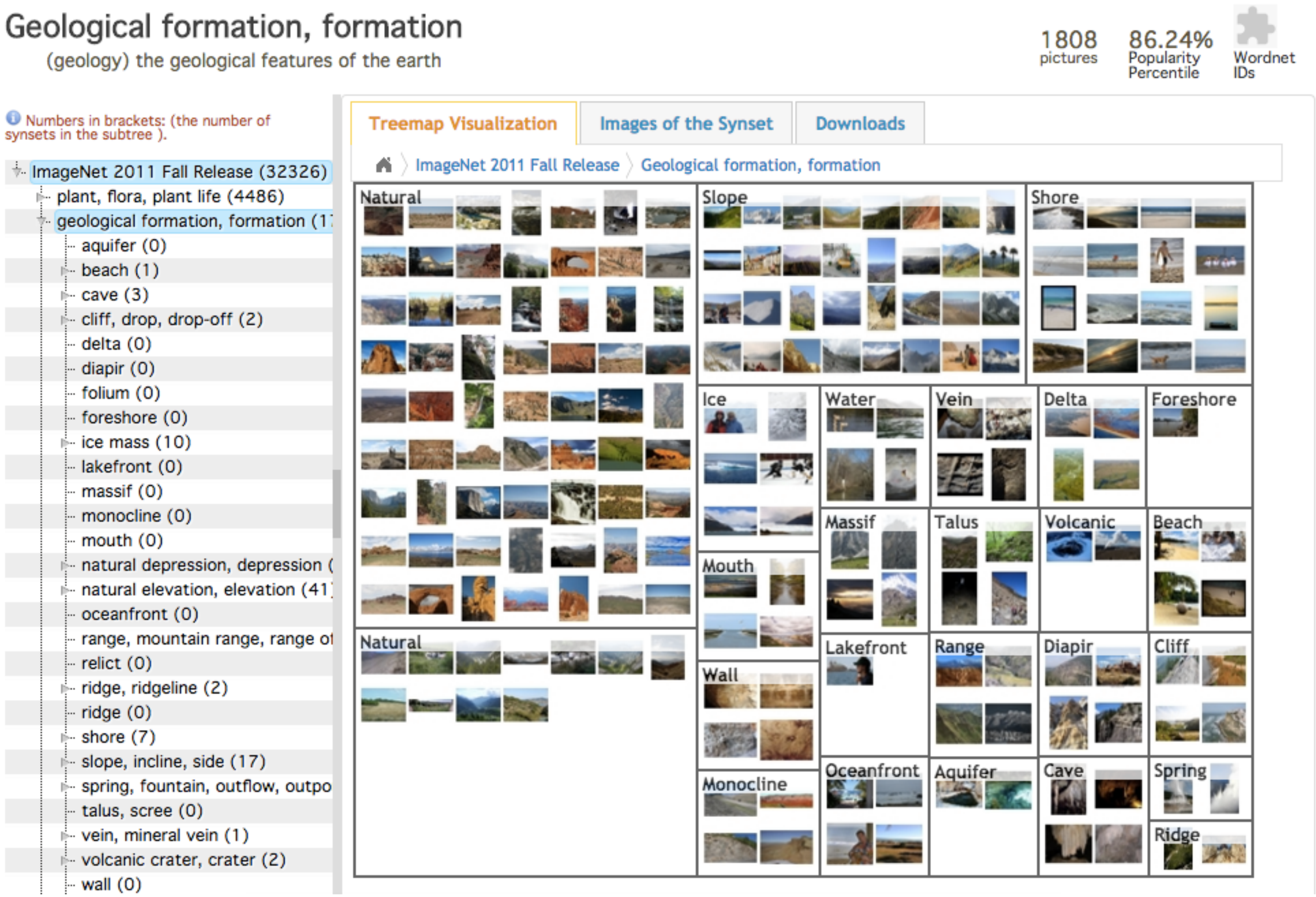
ImageNet uses the hierarchical structure of WordNet [9]. Each meaningful concept in WordNet, possibly described by multiple words or word phrases, is called a "synonym set" or "synset". There are around 80,000 noun synsets

CVPR '09

What is ImageNet?

- Large dataset, v1 in 2009
- Object classification (among others):
  - Input: image
  - Label: synsets from WordNet
- ~14M images currently
- http://www.image-net.org

What is ImageNet?



Why is ImageNet Important?


ATURED QUARTZ EMAI

IT'S NOT ABOUT THE ALGORITHM

The data that transformed AI research—and possibly the world

By Dave Gershgorn • July 26, 2017

link

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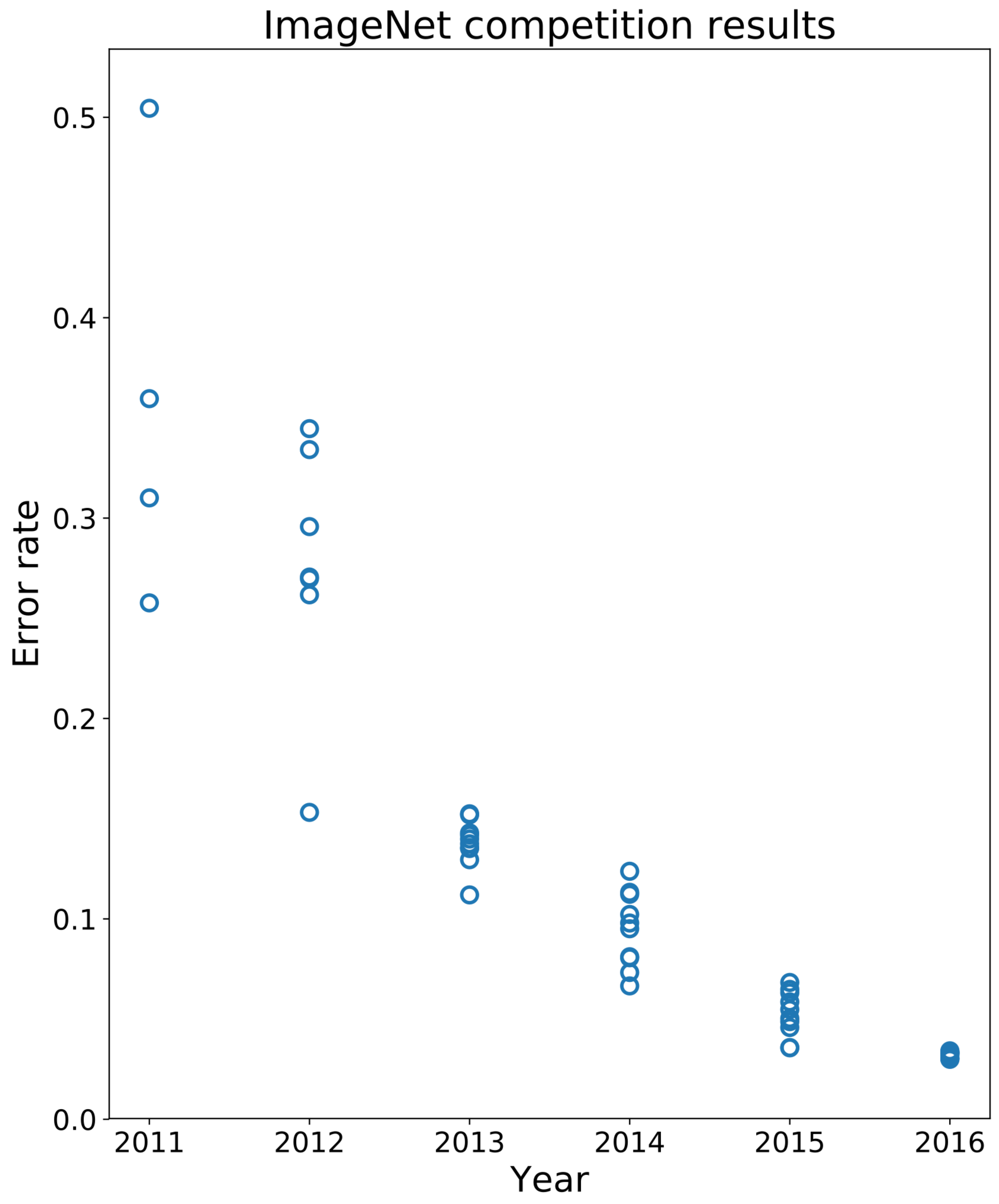
1. Deep learning
2. Transfer learning

ILSVRC

- ImageNet Large Scale Visual Recognition Challenge
- Annual competition on standard benchmark
  - 2010-2017
- ~1.2M training images, 1000 categories
- http://www.image-net.org/challenges/LSVRC/

ILSVRC results



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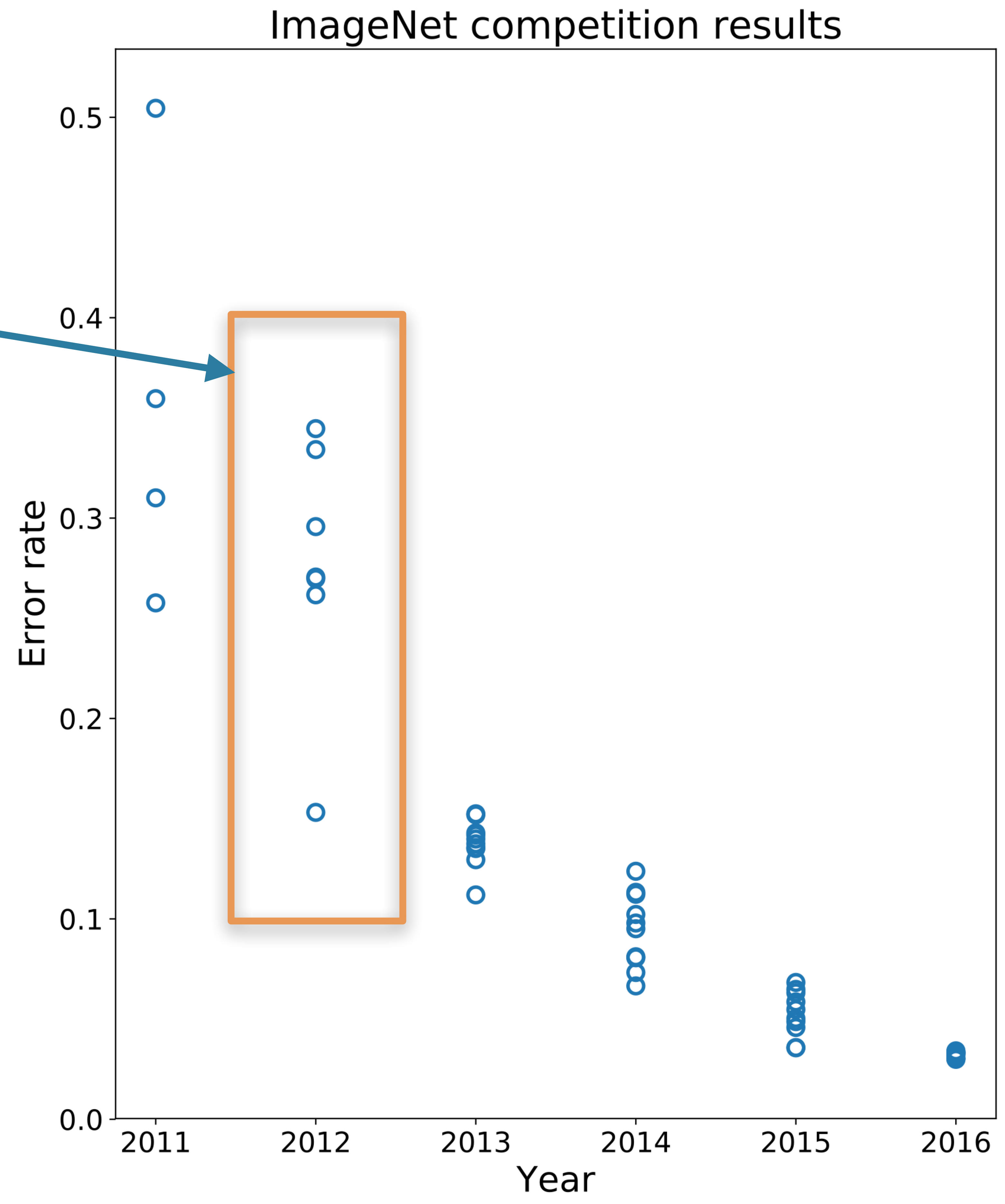
ILSVRC results

What happened in 2012?



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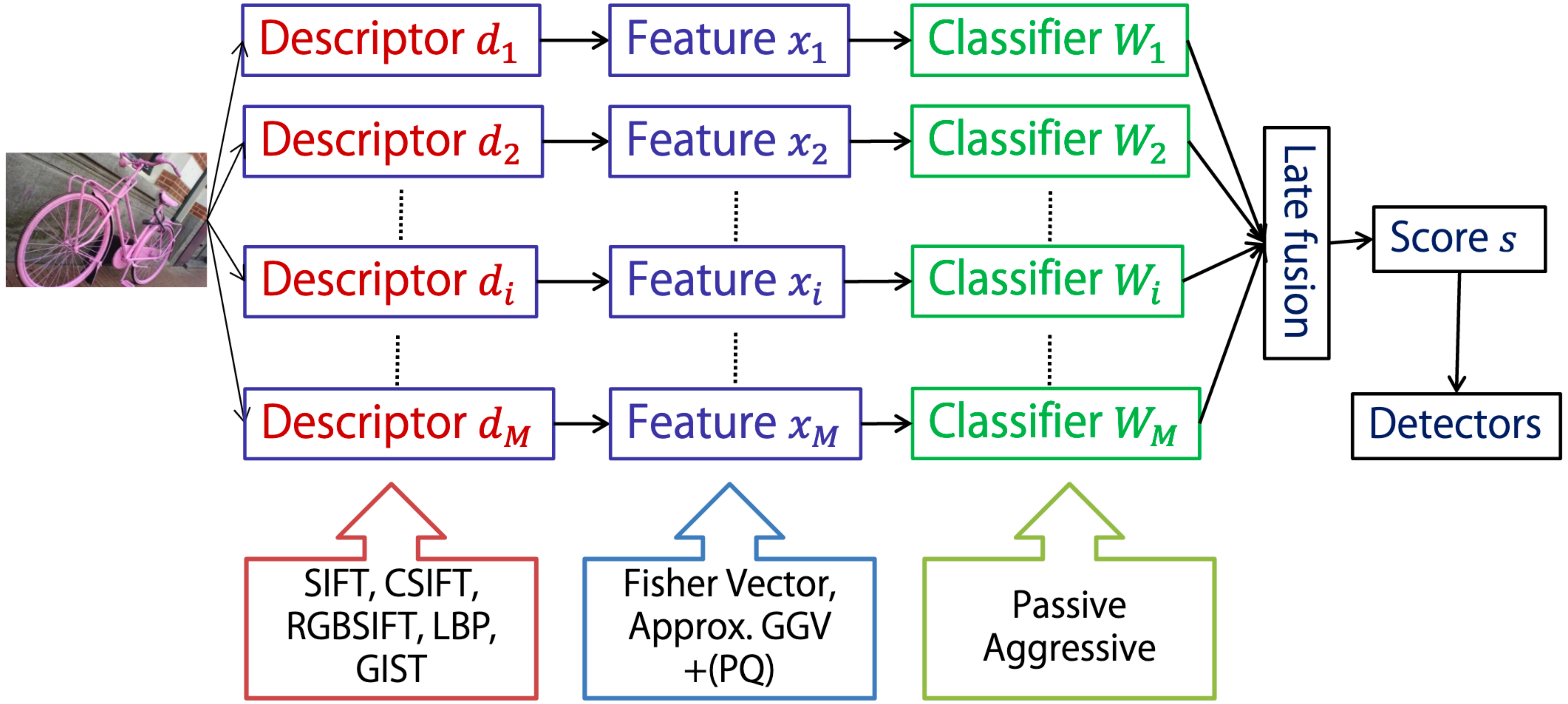
ILSVRC 2012: runner-up

Fisher based features + Multi class linear classifiers



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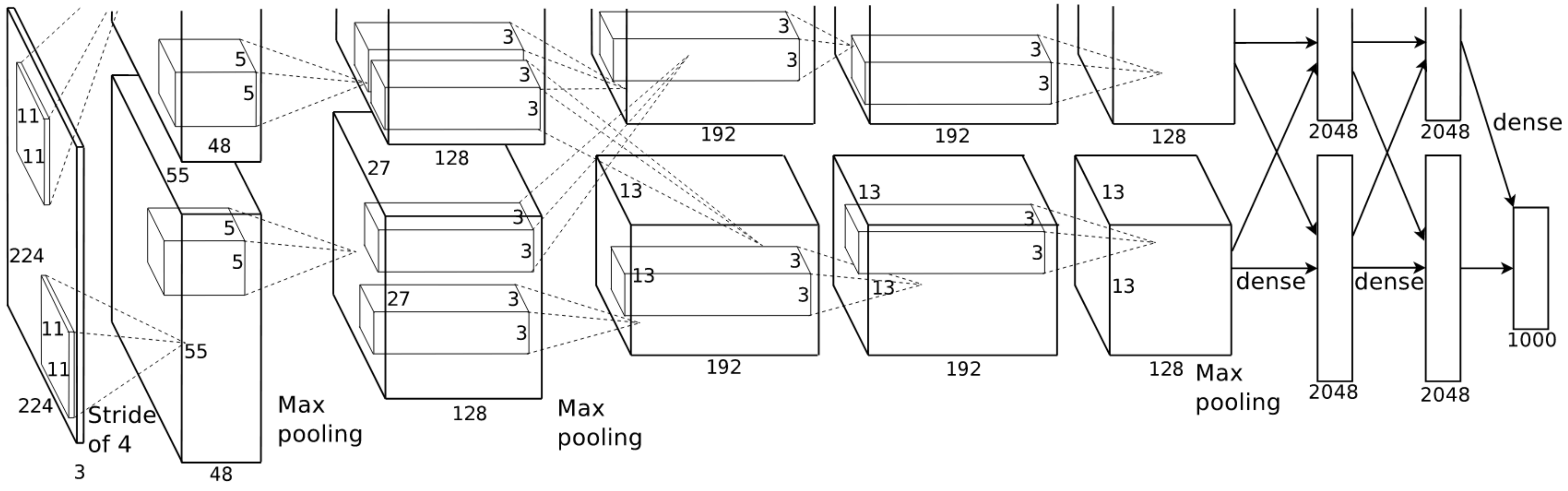
ILSVRC 2012: winner



ImageNet Classification with Deep Convolutional Neural Networks

Alex Krizhevsky
University of Toronto
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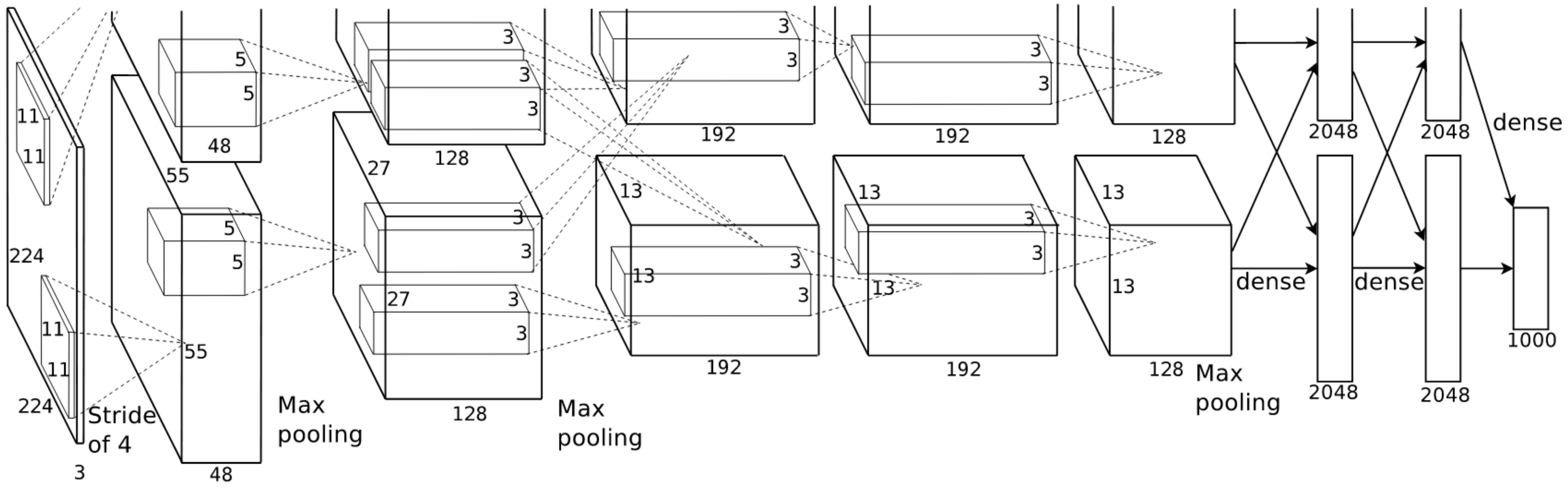
Ilya Sutskever
University of Toronto
ilya@cs.utoronto.ca

Geoffrey E. Hinton
University of Toronto
hinton@cs.utoronto.ca

NeurIPS 2012 paper

ILSVRC 2012: winner



"AlexNet"

ImageNet Classification with Deep Convolutional Neural Networks

Alex Krizhevsky
University of Toronto
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ilya@cs.utoronto.ca

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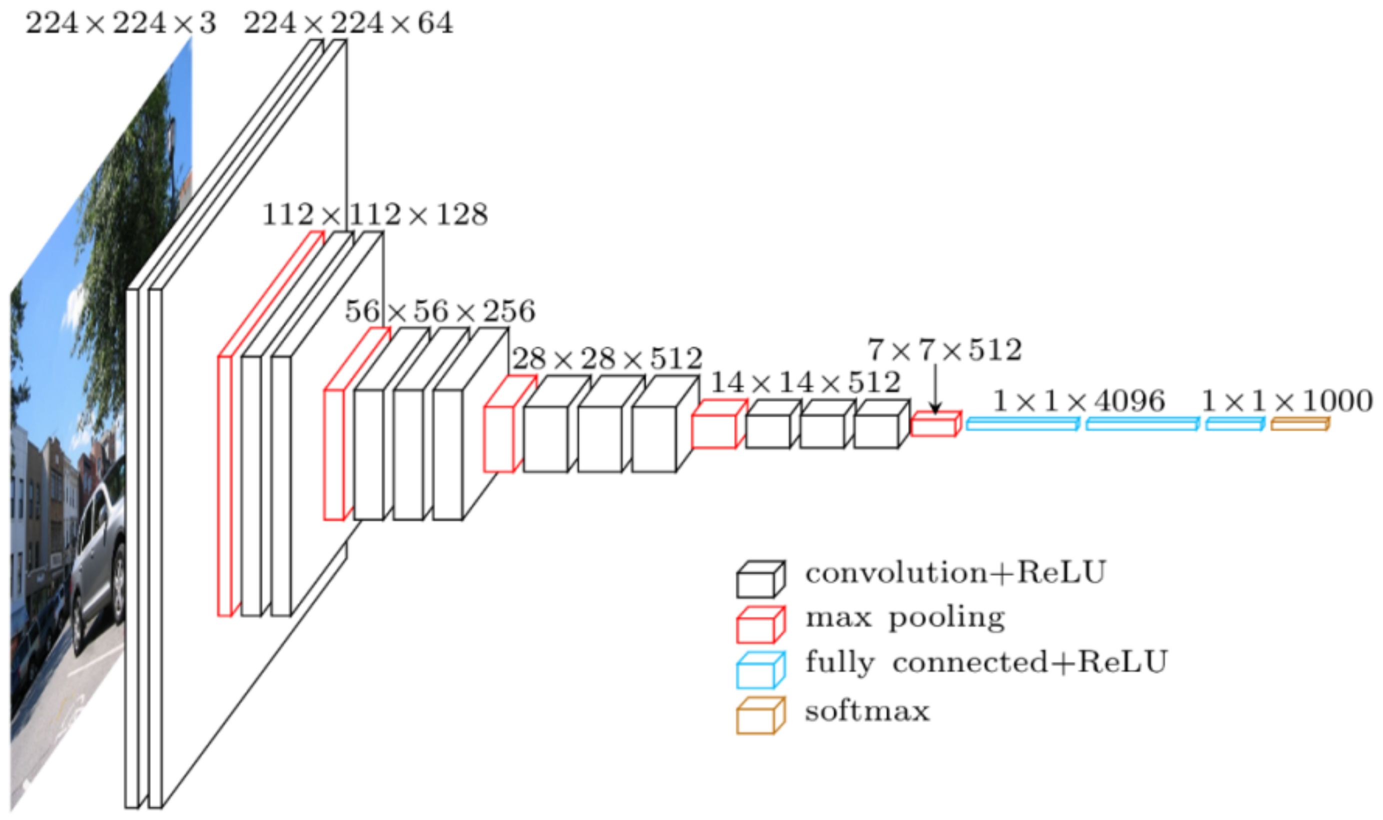
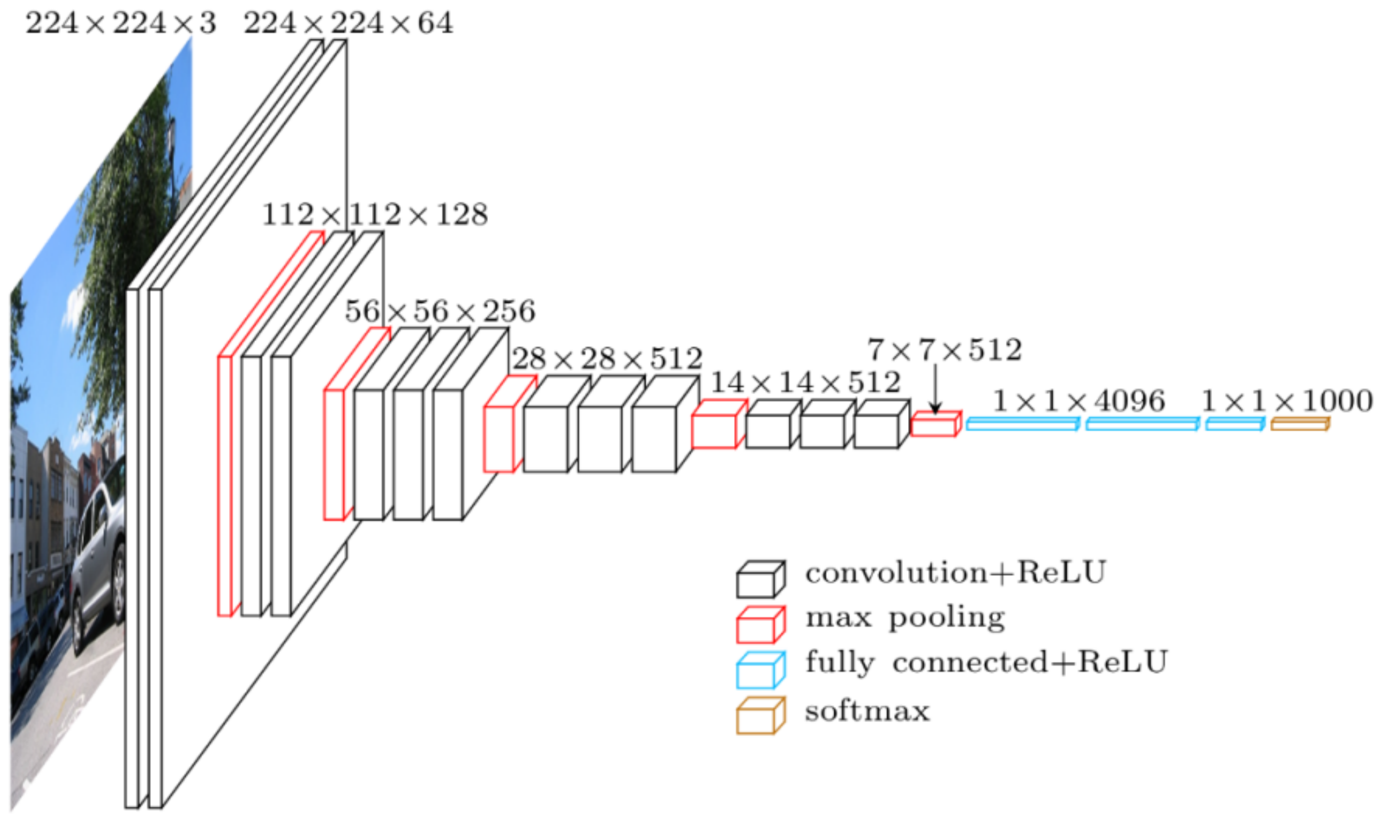
NeurIPS 2012 paper

Deep Learning Tidal Wave

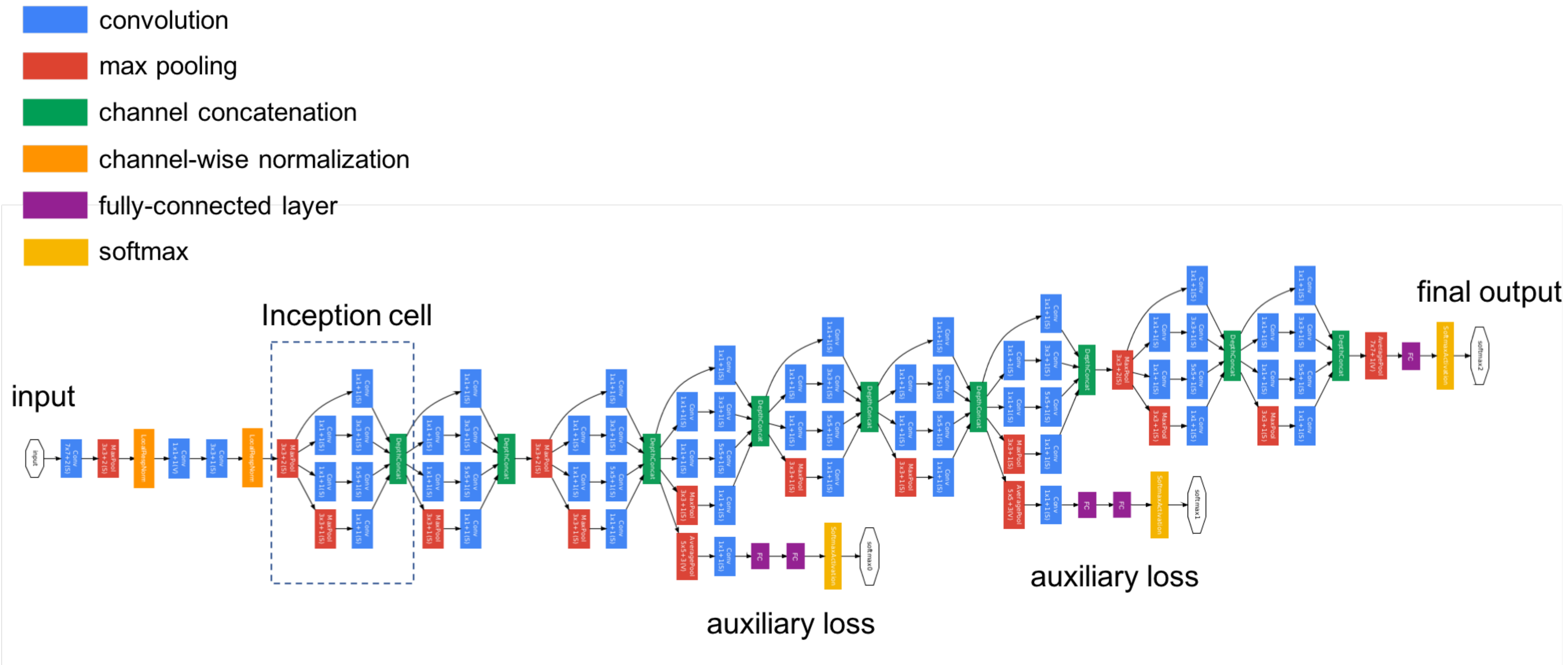


[VGG16]

Deep Learning Tidal Wave

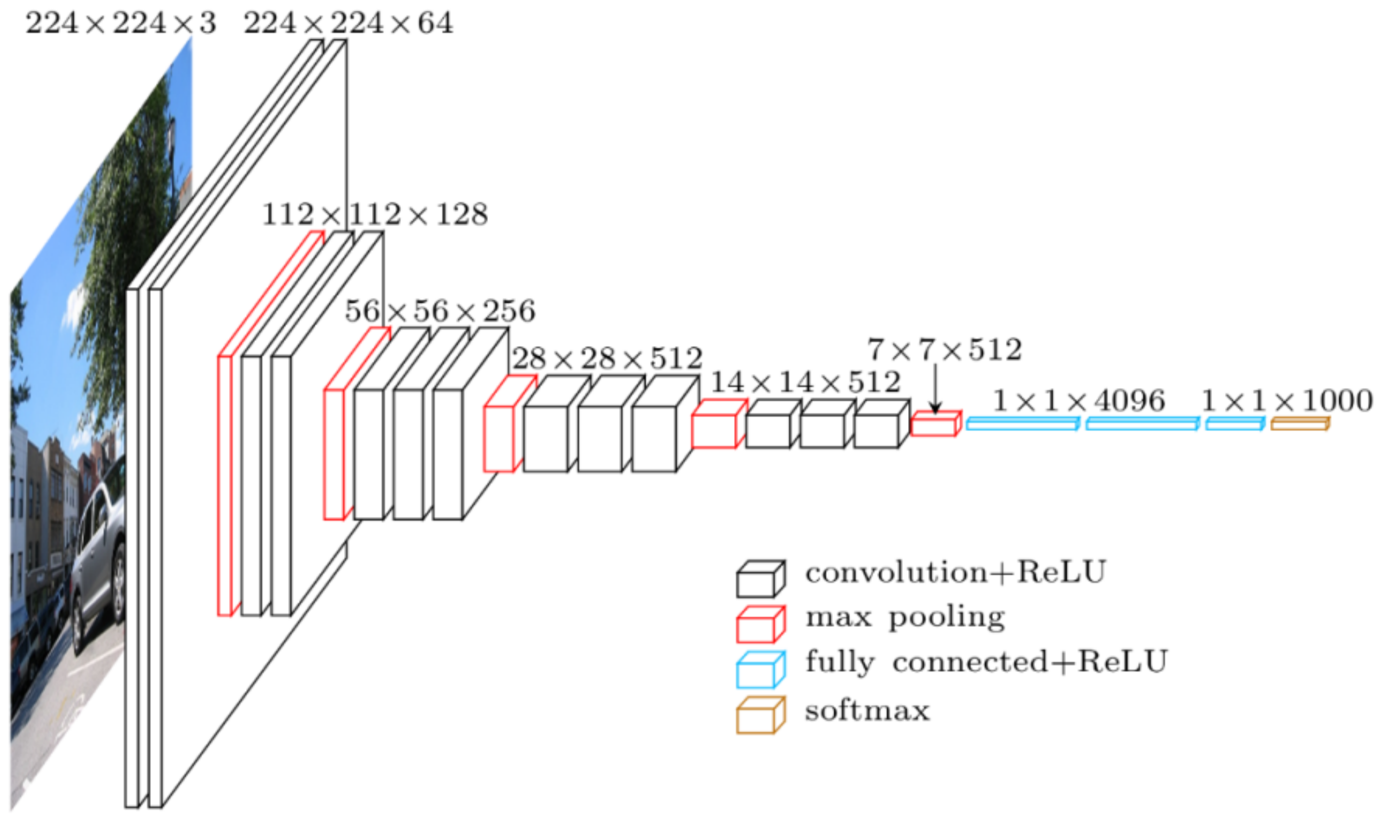


VGG16

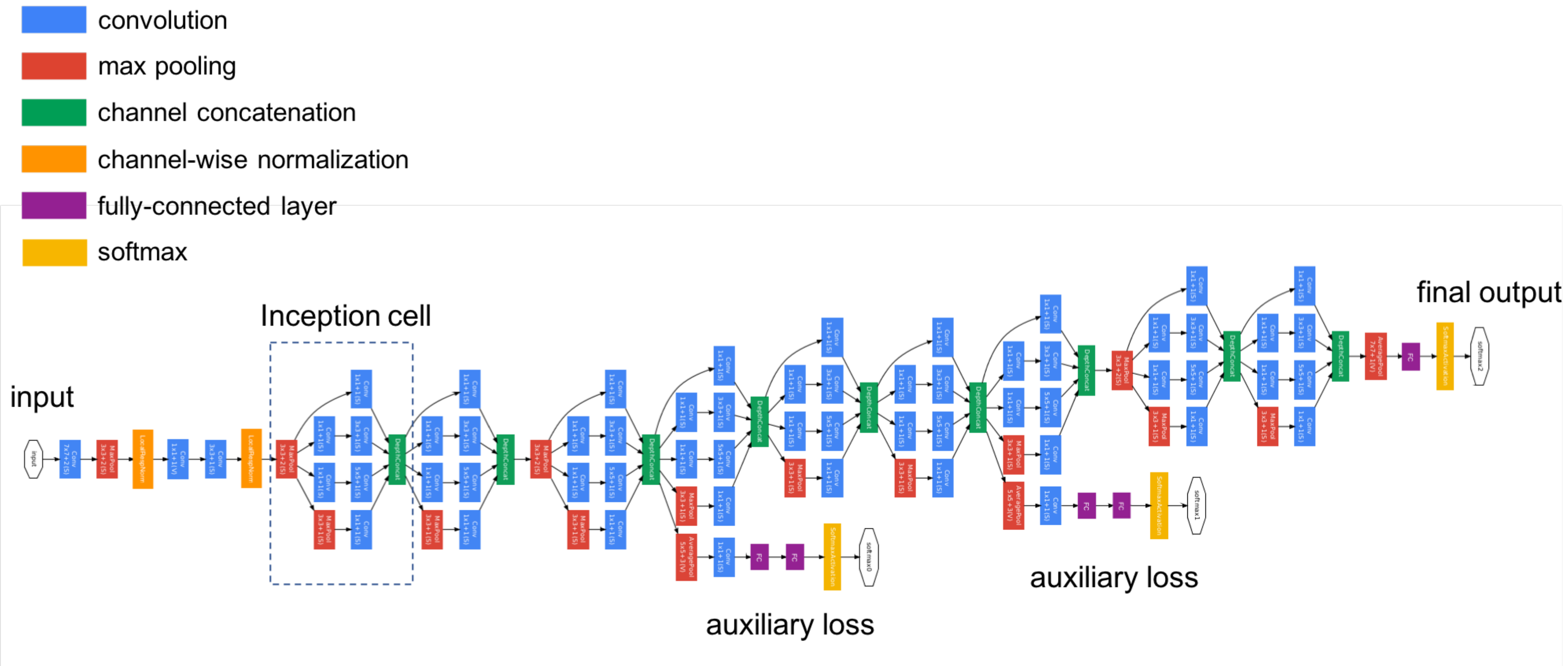


Inception

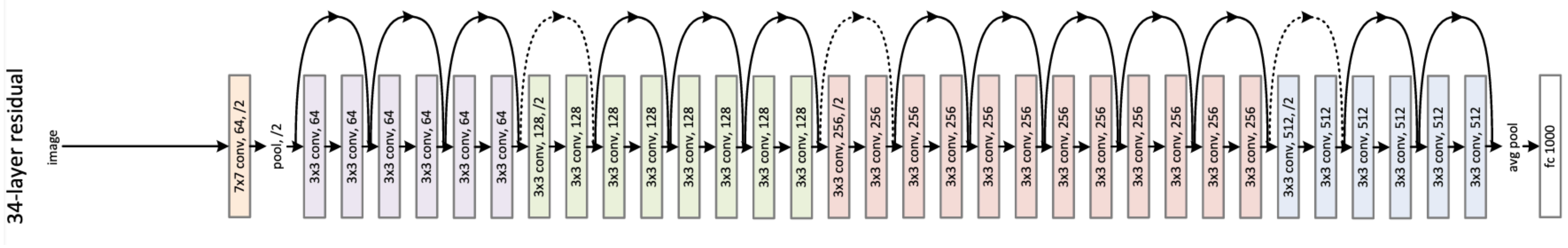
Deep Learning Tidal Wave



VGG16



Inception



ResNet (34 layers above; up to 152 in paper)

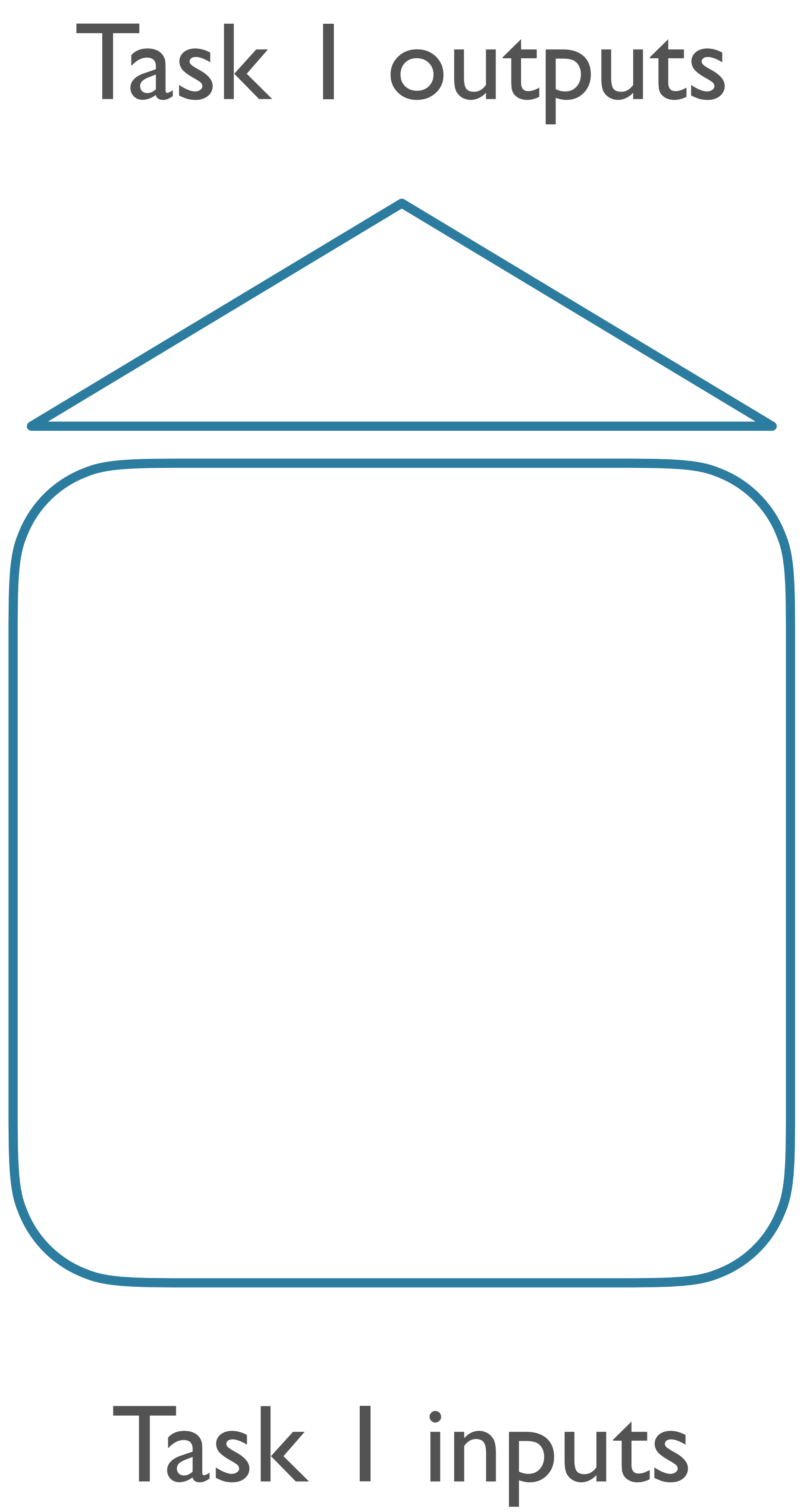
Transfer Learning

CNN Features off-the-shelf: an Astounding Baseline for Recognition

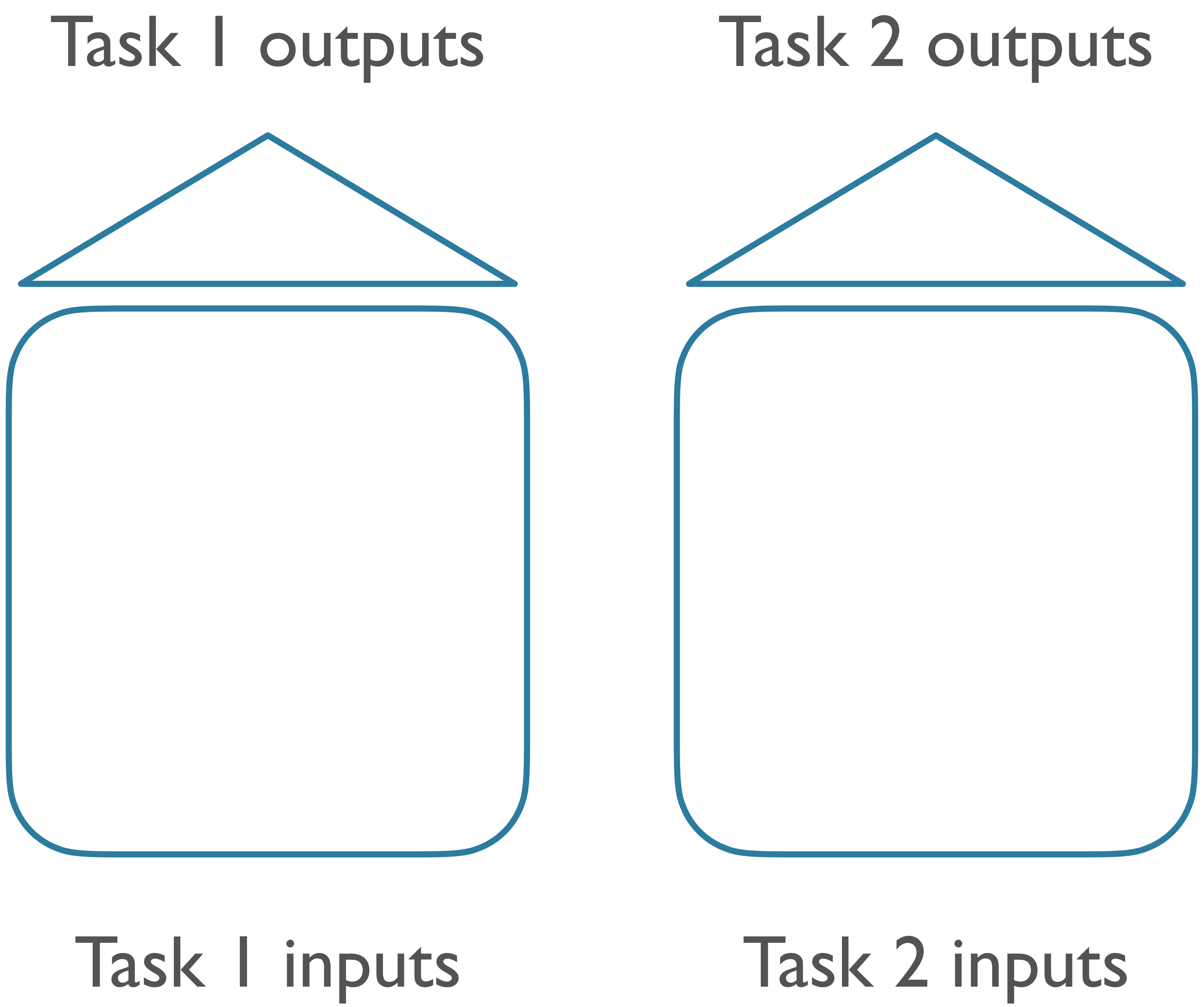
Ali Sharif Razavian   Hossein Azizpour   Josephine Sullivan   Stefan Carlsson
CVAP, KTH (Royal Institute of Technology)
Stockholm, Sweden
{razavian,azizpour,sullivan,stefanc}@csc.kth.se

"We use features extracted from the `OverFeat` network as a generic image representation to tackle the diverse range of recognition tasks of object image classification, scene recognition, fine grained recognition, attribute detection and image retrieval applied to a diverse set of datasets. We selected these tasks and datasets as they grad-ually move further away from the original task and data the `OverFeat` network was trained to solve [cf. ImageNet]. Astonishingly, we report consistent superior results compared to the highly tuned state-of-the-art systems in all the visual classification tasks on various datasets"

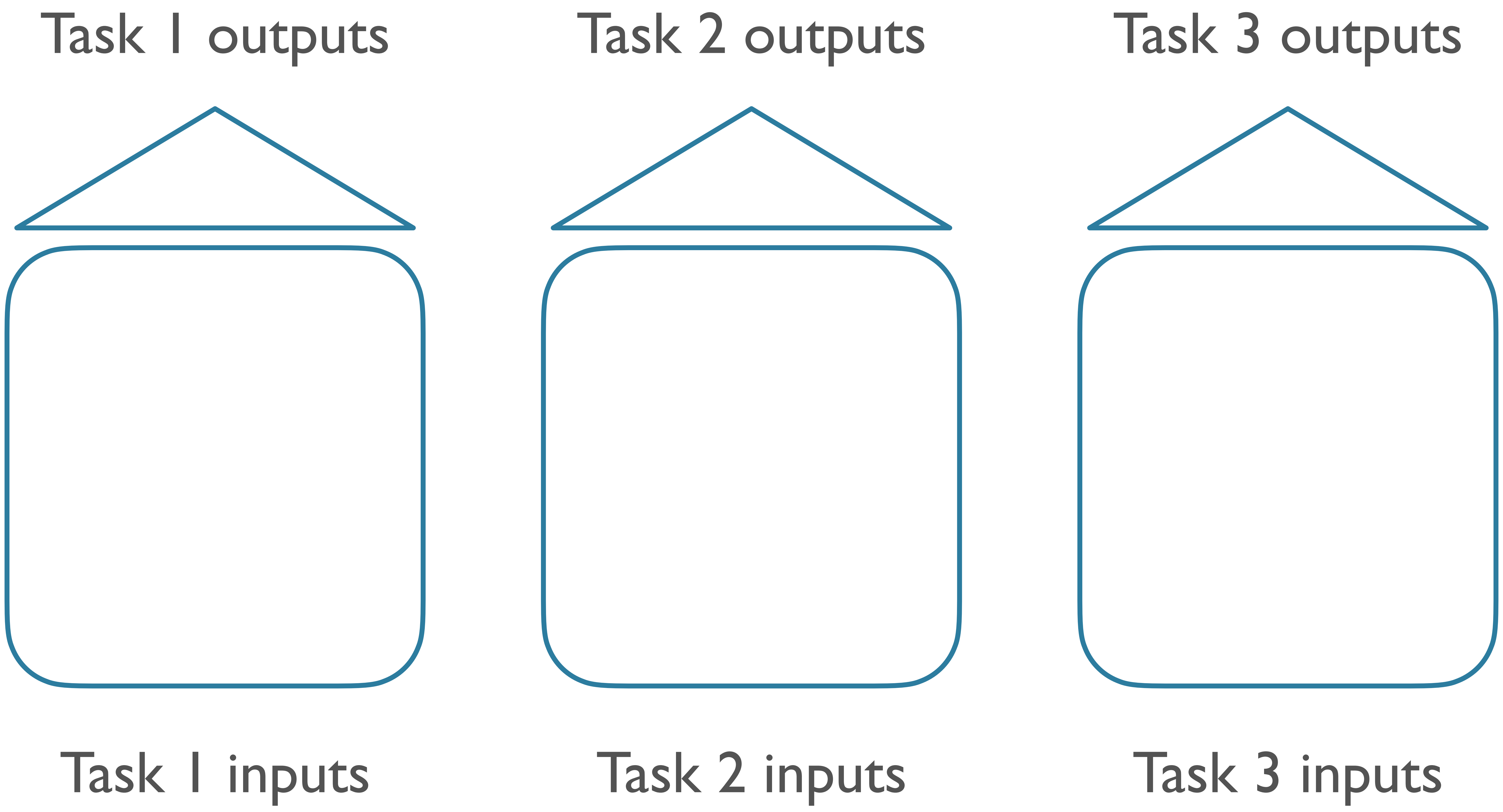
Standard Learning



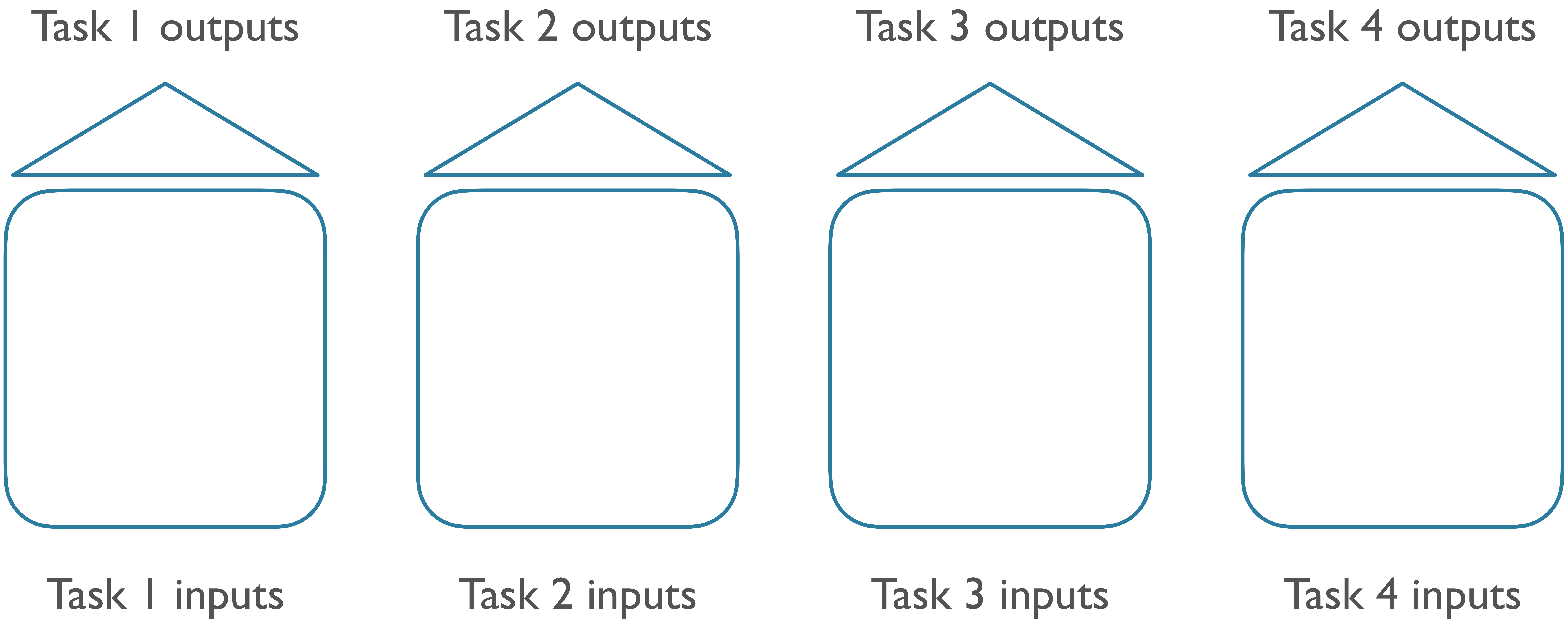
Standard Learning



Standard Learning



Standard Learning

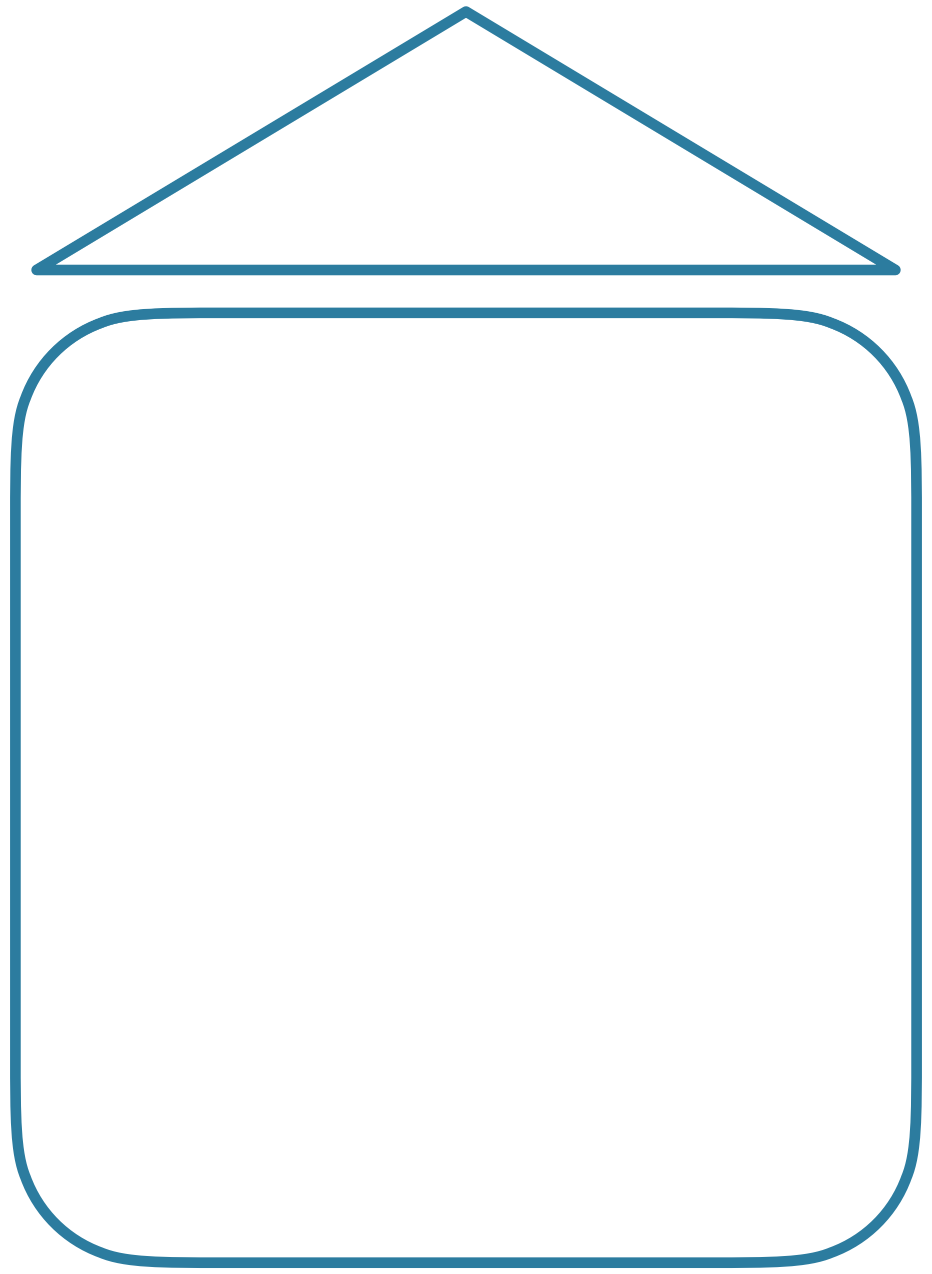


Standard Learning

- New task = new model
- Expensive!
  - Training time
  - Storage space
  - Data availability
    - Can be impossible in low-data regimes

Transfer Learning

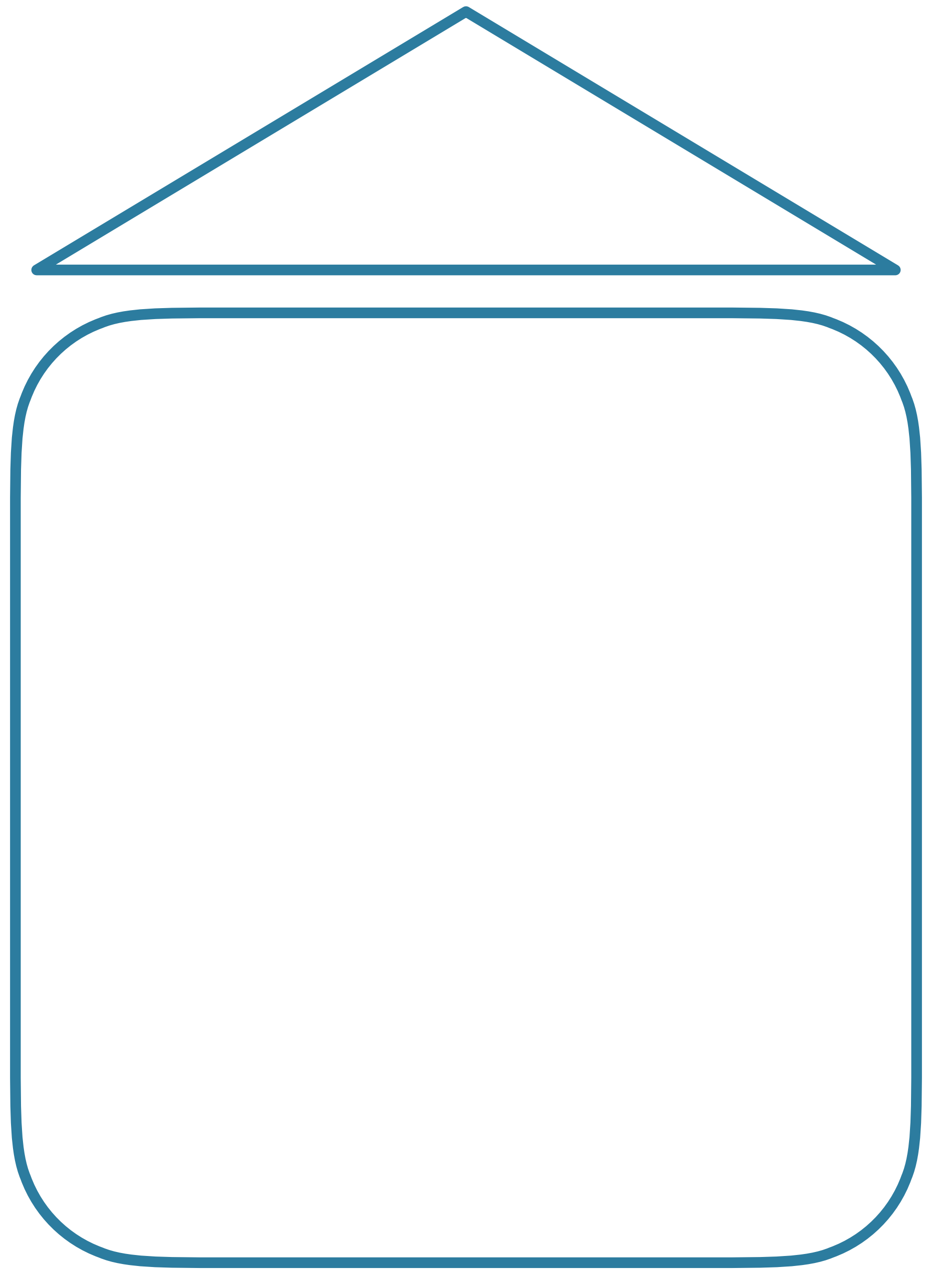
“pre-training” task outputs



“pre-training” task inputs

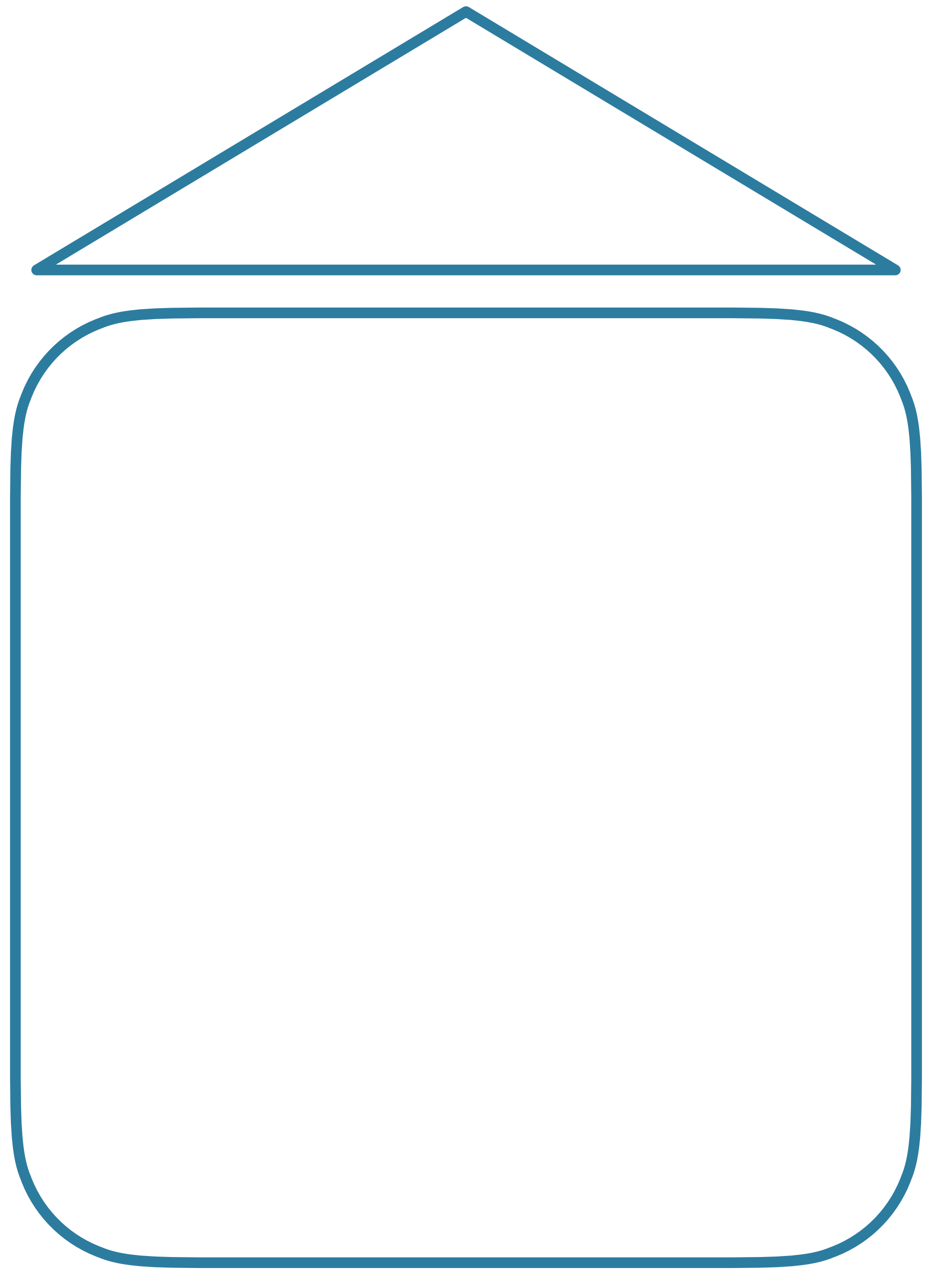
Transfer Learning

“pre-training” task outputs



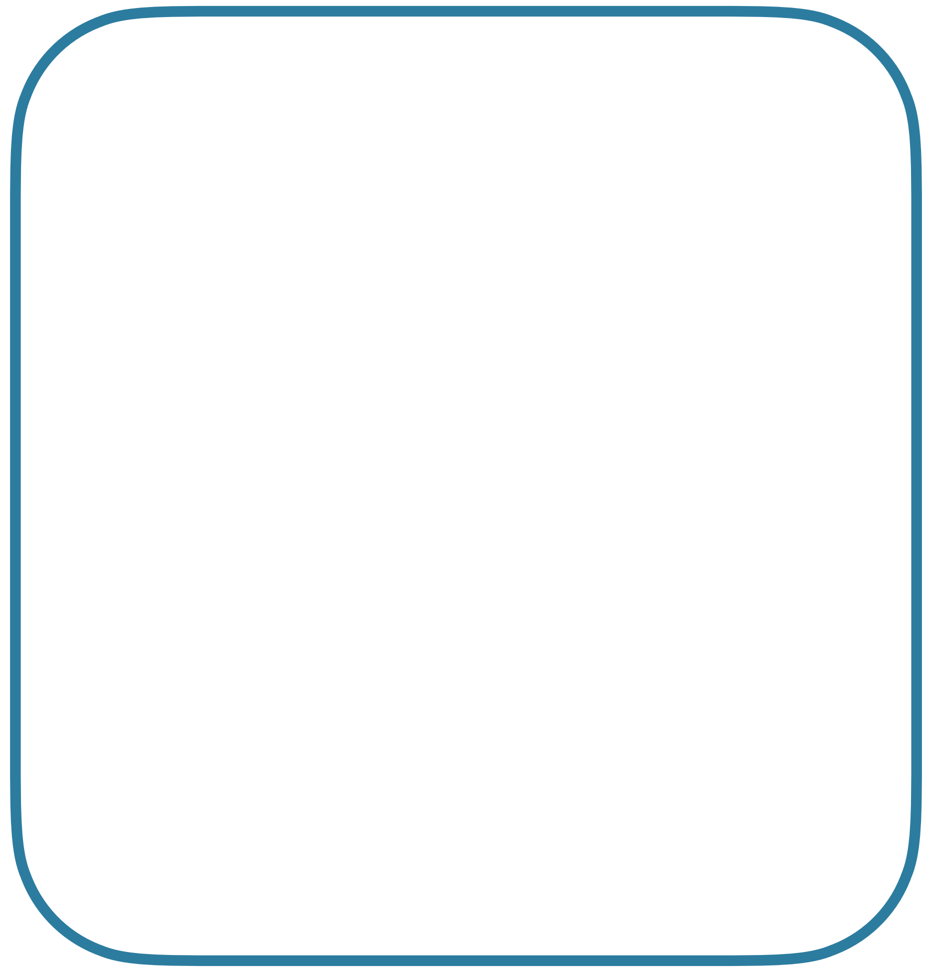
Transfer Learning

“pre-training” task outputs



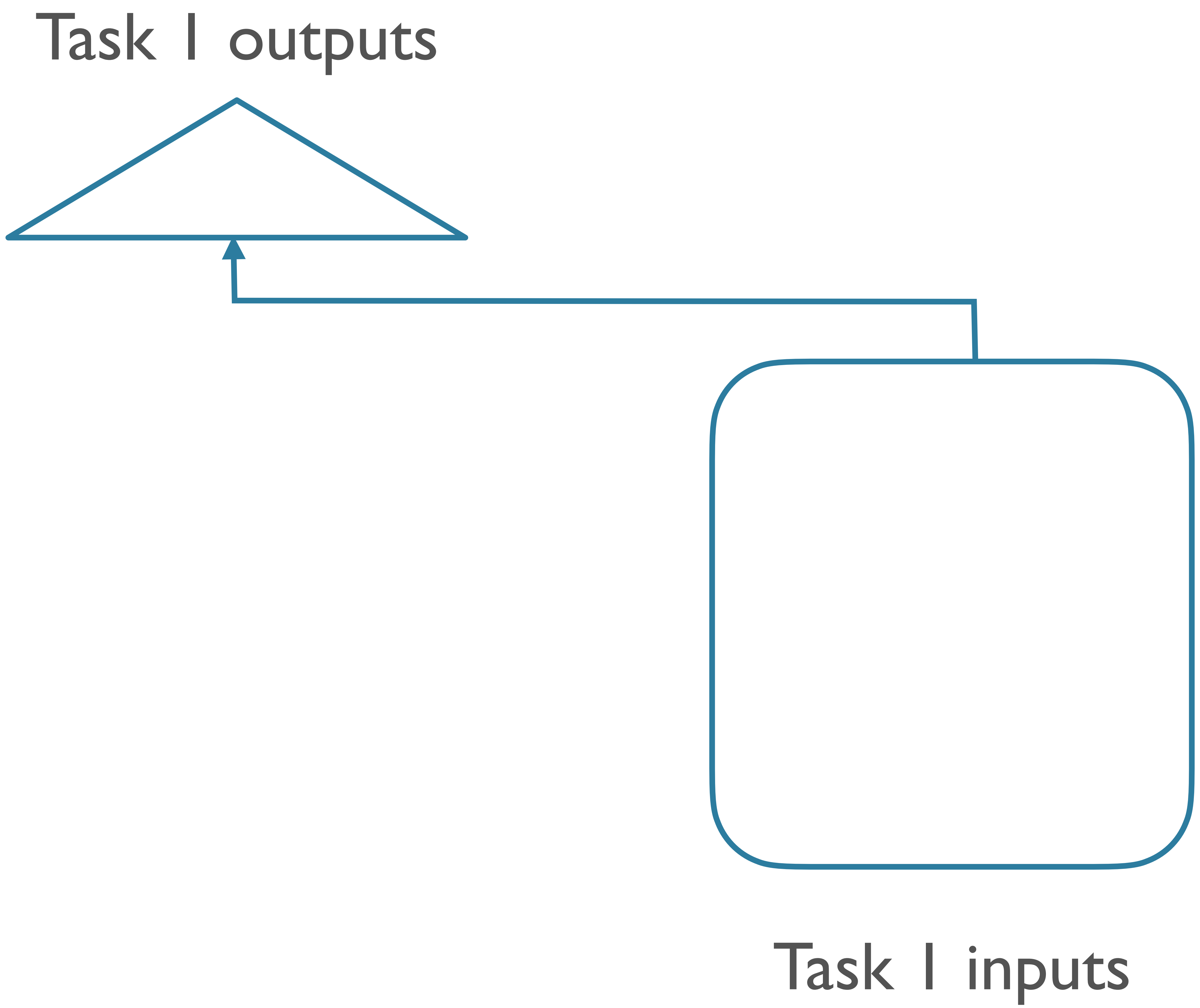
Task 1 inputs

Transfer Learning

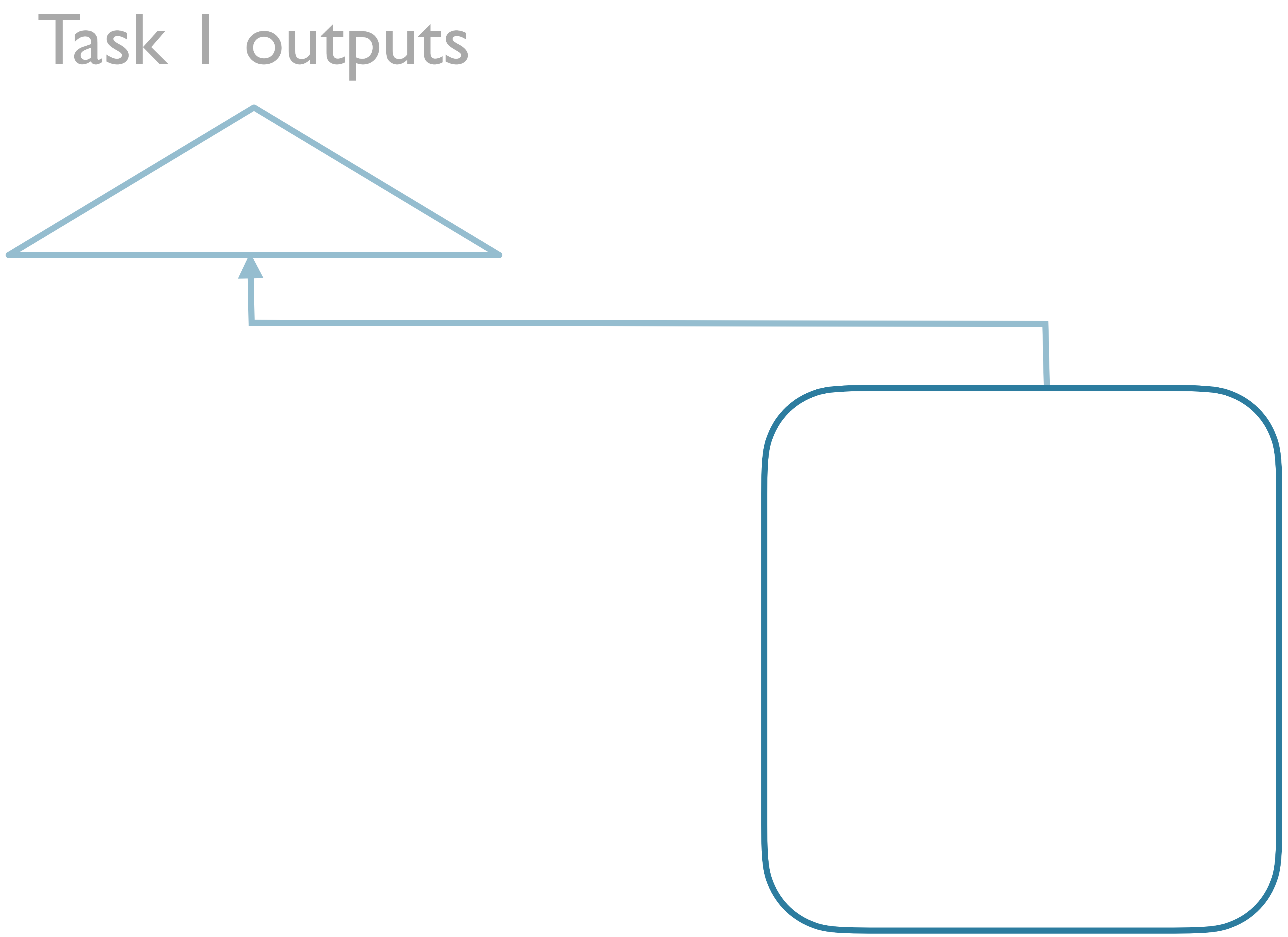


Task 1 inputs

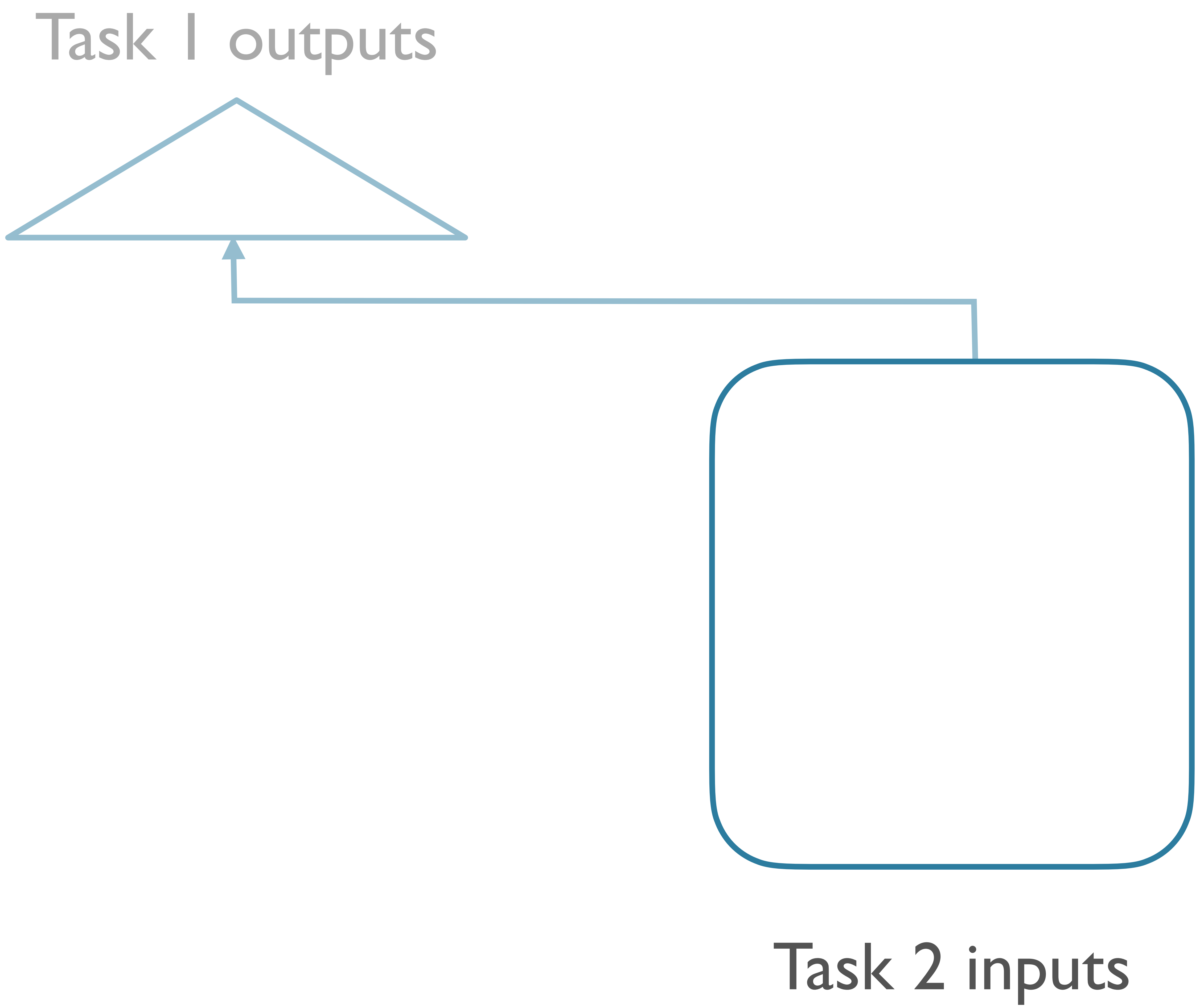
Transfer Learning



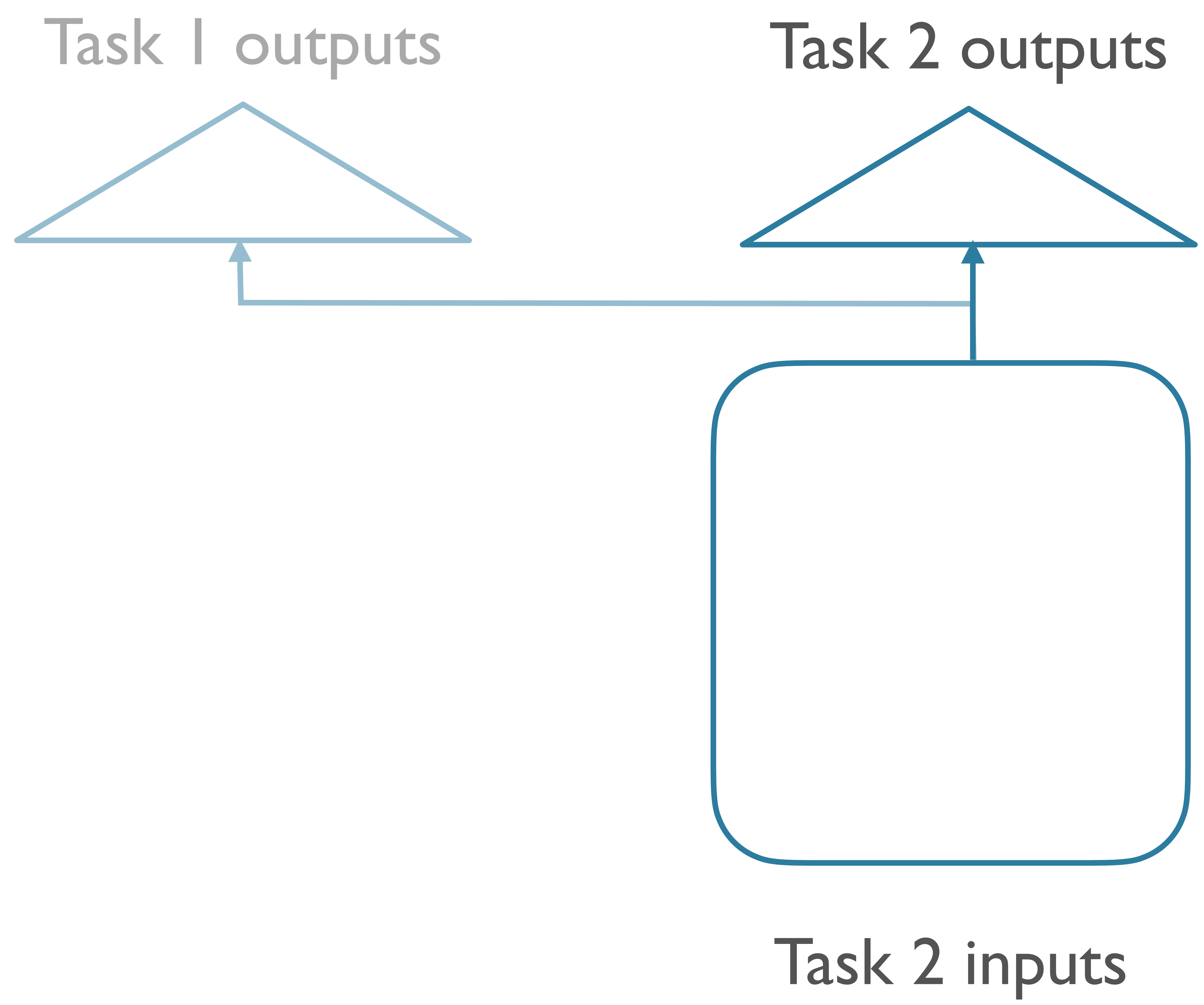
Transfer Learning



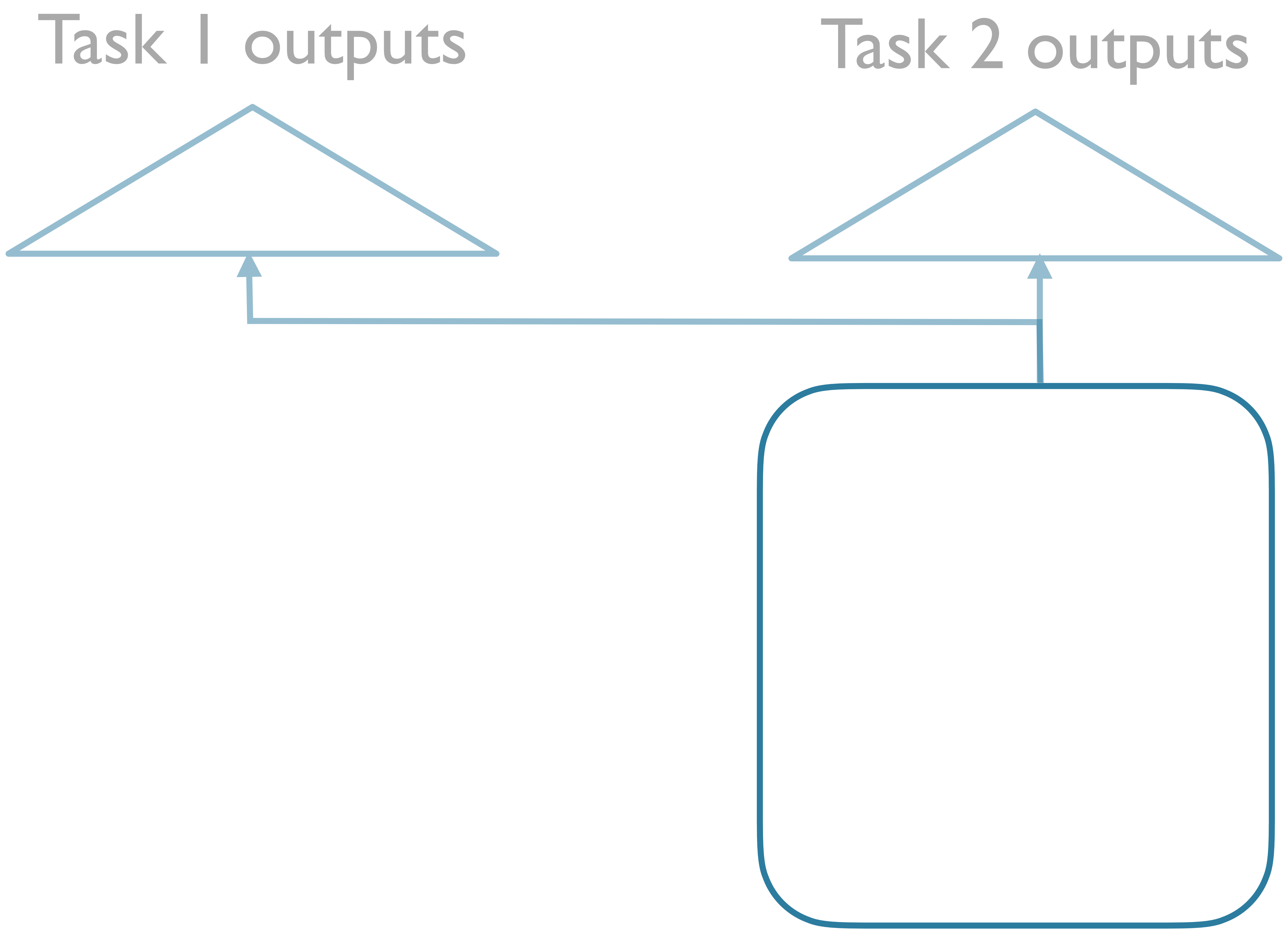
Transfer Learning



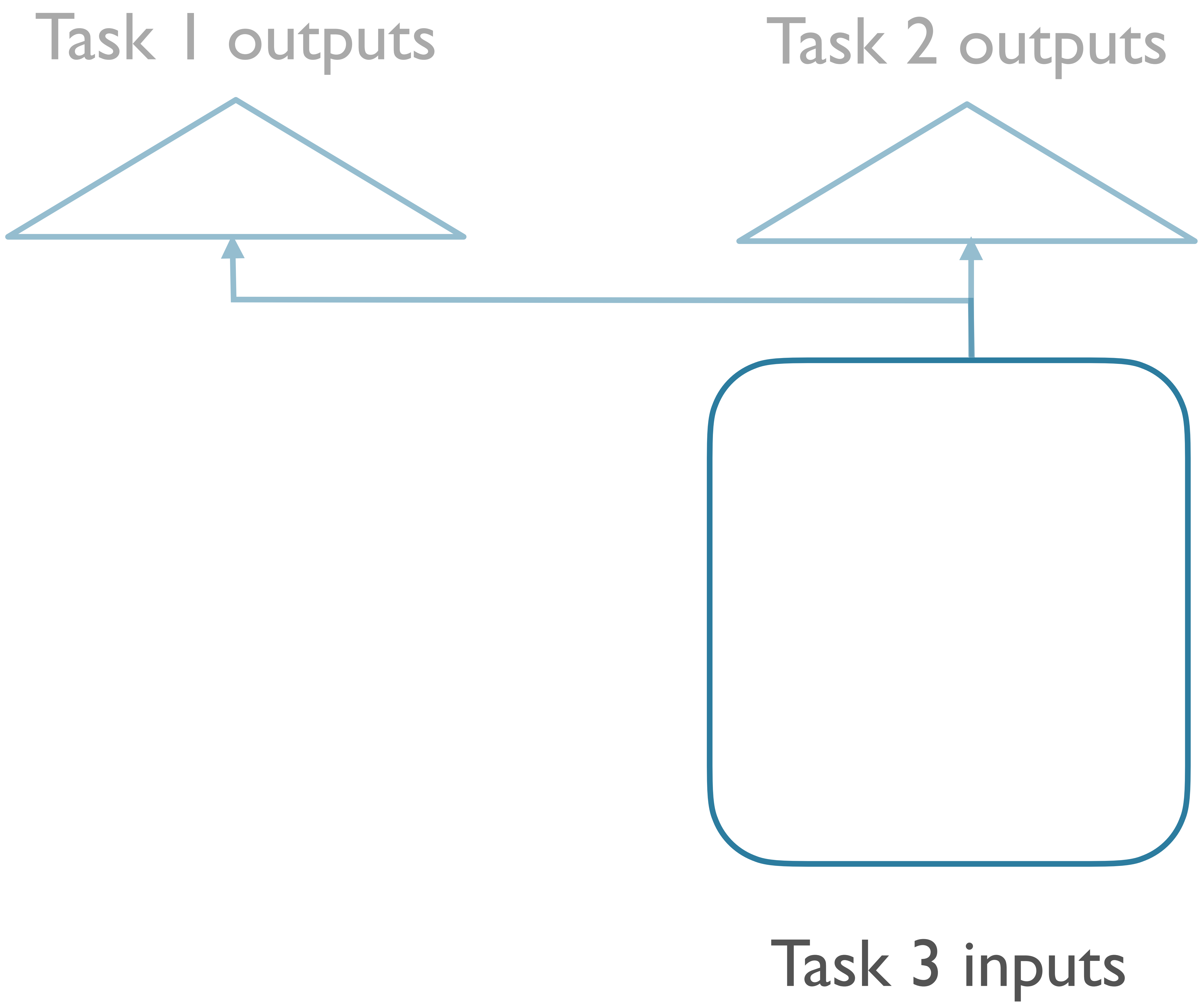
Transfer Learning



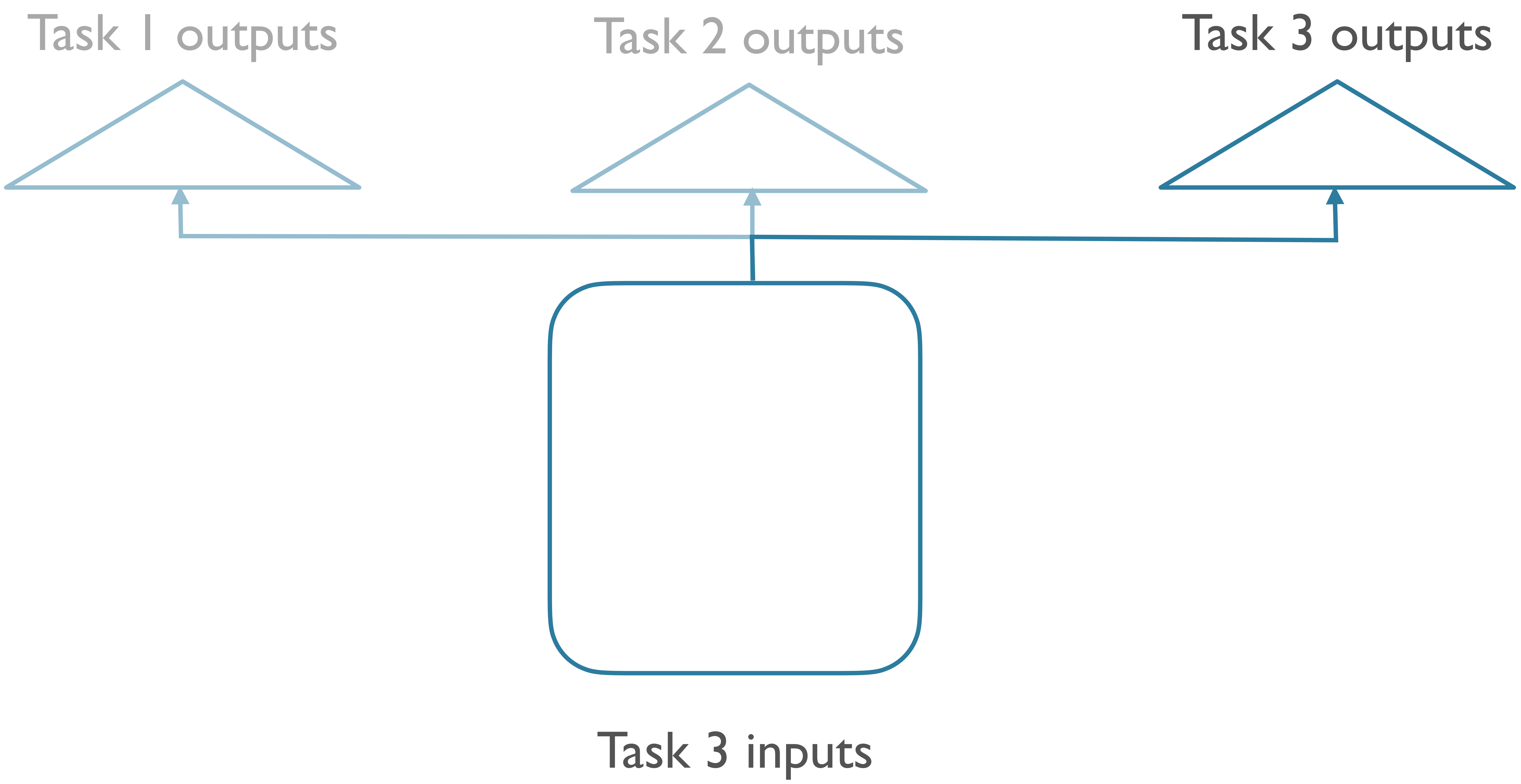
Transfer Learning



Transfer Learning



Transfer Learning



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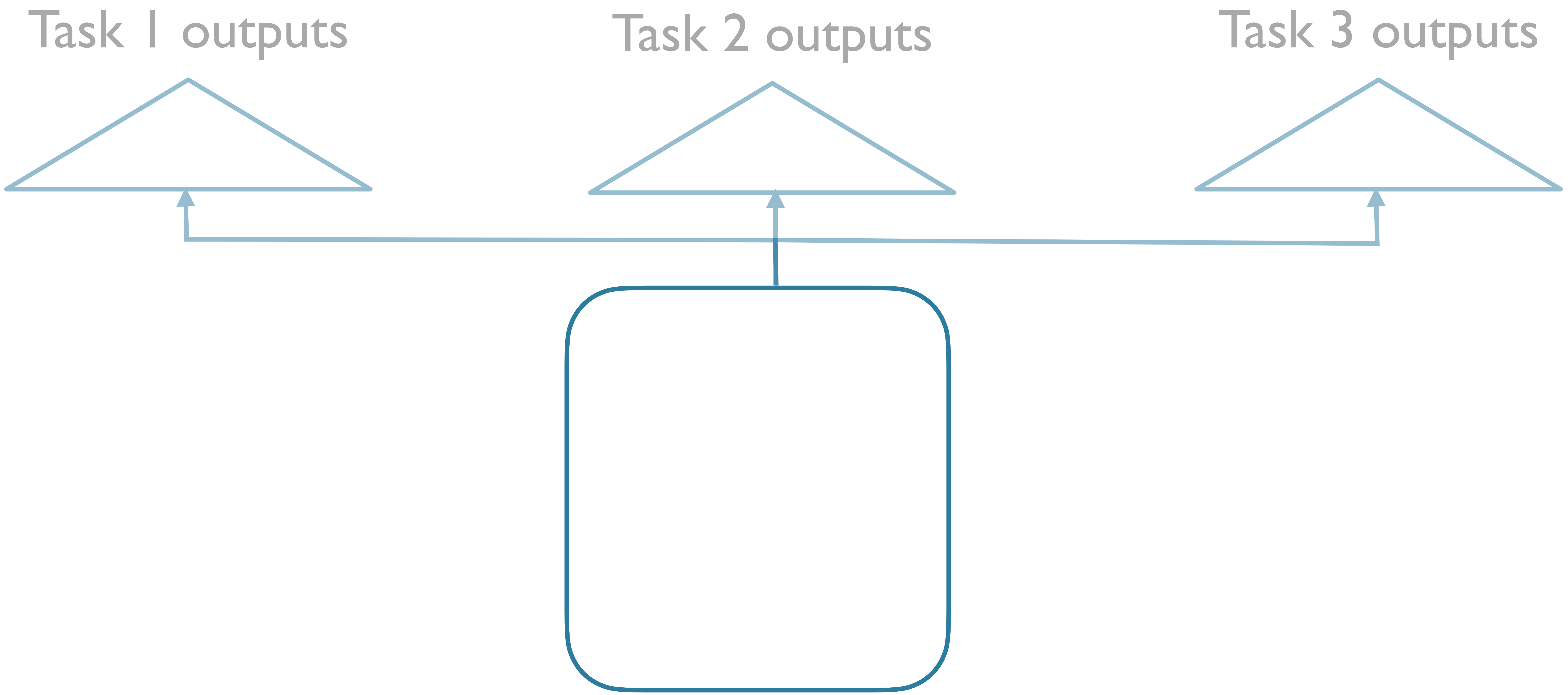
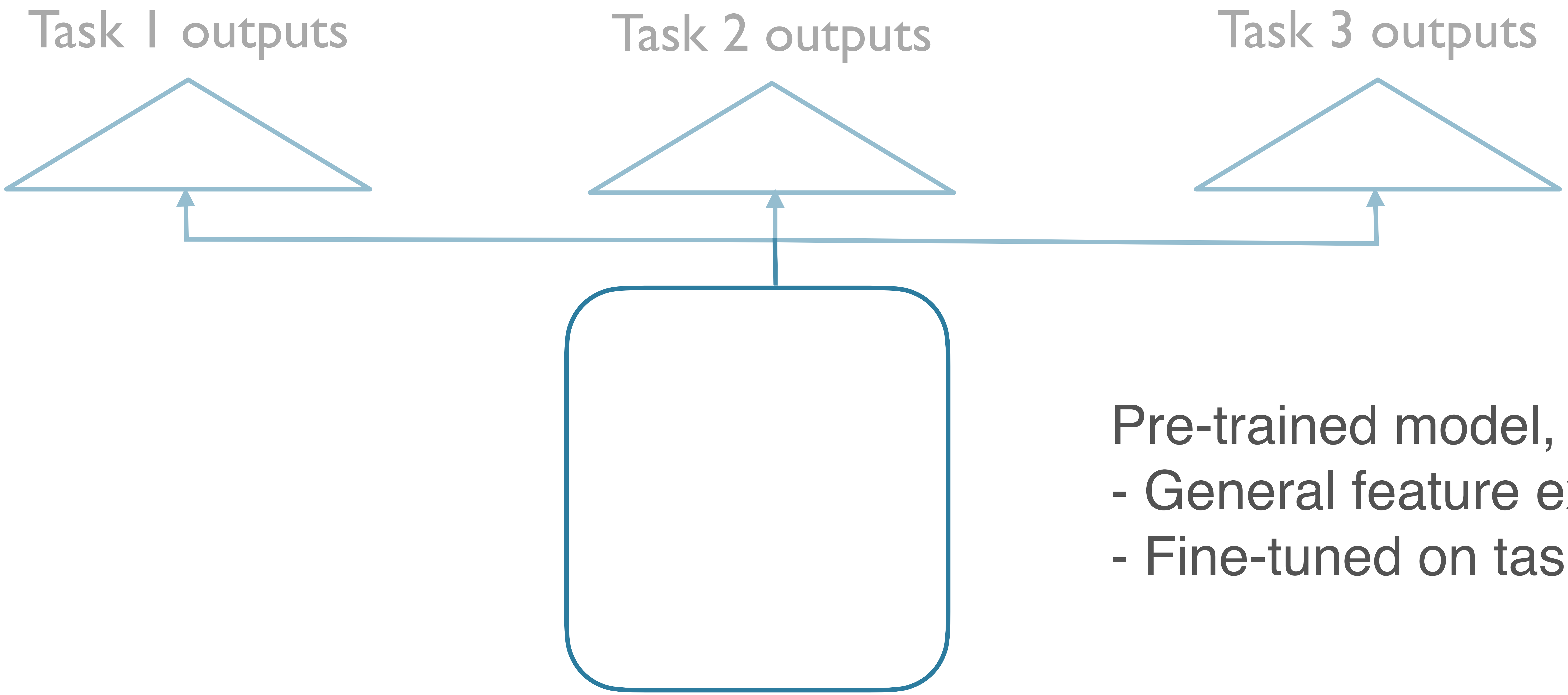


Transfer Learning

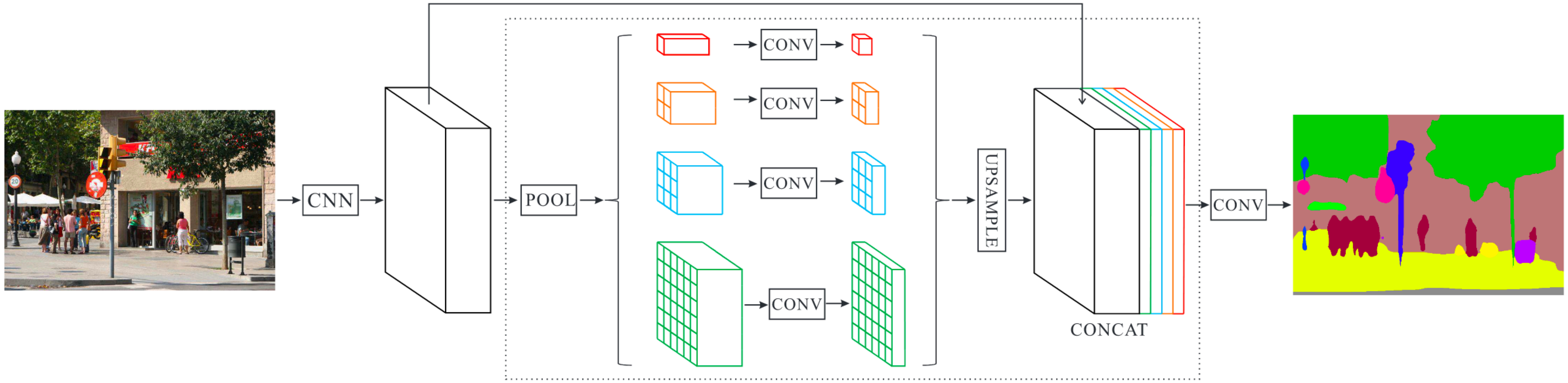


Pre-trained model, either:
- General feature extractor
- Fine-tuned on tasks

Example: Scene Parsing

(a) Image (b) Ground Truth

Example: Scene Parsing

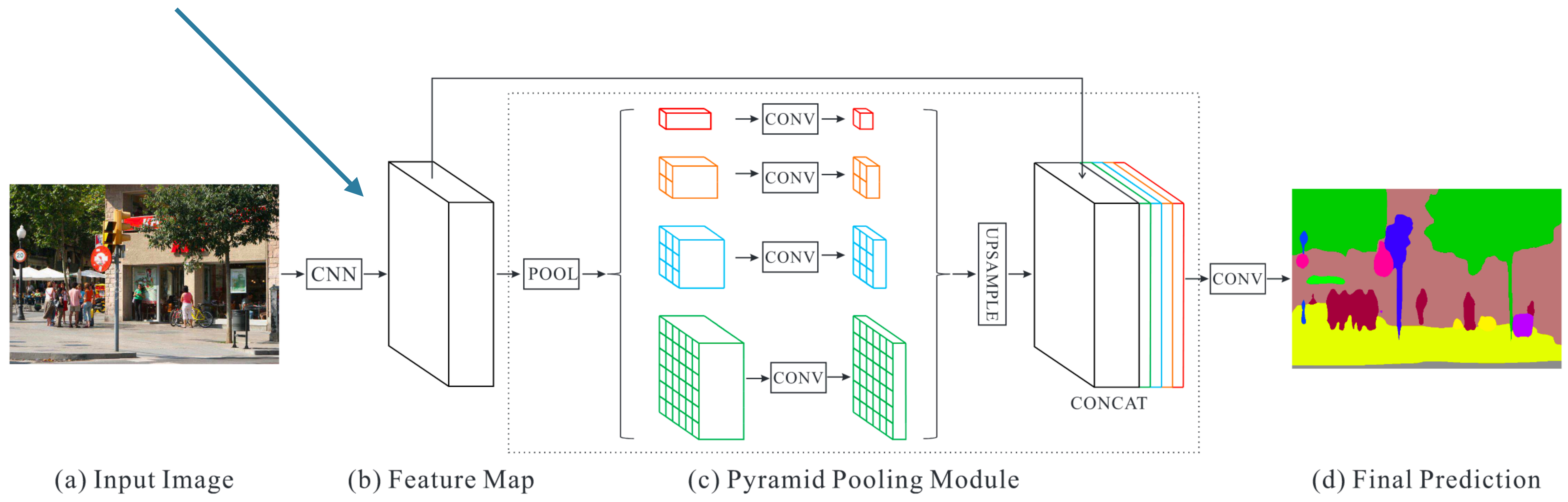


(a) Input Image (b) Feature Map (c) Pyramid Pooling Module (d) Final Prediction

[CVPR '17 paper]

Example: Scene Parsing

Pre-trained ResNet



CVPR '17 paper

Transfer Learning in NLP

Where to transfer *from*?

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- Goal: find a linguistic task that will build general-purpose / *transferable* representations

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- Possibilities:

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- Possibilities:
  - Constituency or dependency parsing

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- Goal: find a linguistic task that will build general-purpose / *transferable* representations
- Possibilities:
  - Constituency or dependency parsing
  - Semantic parsing

Where to transfer *from*?

- Goal: find a linguistic task that will build general-purpose / *transferable* representations
- Possibilities:
  - Constituency or dependency parsing
  - Semantic parsing
  - Machine translation

Where to transfer *from*?

- Goal: find a linguistic task that will build general-purpose / *transferable* representations
- Possibilities:
  - Constituency or dependency parsing
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  - Machine translation
  - QA

Where to transfer *from*?

- Goal: find a linguistic task that will build general-purpose / *transferable* representations
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  - Constituency or dependency parsing
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  - …

Where to transfer *from*?

- Goal: find a linguistic task that will build general-purpose / *transferable* representations
- Possibilities:
  - Constituency or dependency parsing
  - Semantic parsing
  - Machine translation
  - QA
  - …
- Scalability issue: all require expensive annotation

Language Modeling

Language Modeling

- Recent innovation: use *language modeling* (a.k.a. next word prediction)
  - [*: we will talk about variations later in the seminar]

Language Modeling

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- Linguistic knowledge:
  - The students were happy because ____ …
  - The student was happy because ____ …

Language Modeling

- Recent innovation: use *language modeling* (a.k.a. next word prediction)
  - [*: we will talk about variations later in the seminar]

- Linguistic knowledge:
  - The students were happy because ____ …
  - The student was happy because ____ …

- World knowledge:
  - The POTUS gave a speech after Ukraine was invaded by _____
  - Seattle lies on the Puget _____

Language Modeling is “Unsupervised”

- An example of “unsupervised” or “semi-supervised” learning
  - NB: I think that “un-annotated” is a better term. Formally, the learning is supervised. But the labels come directly from the “raw” data, not an annotator.
- E.g.: “Today is the first day of 575.”
  - (<s>, Today)
  - (<s> Today, is)
  - (<s> Today is, the)
  - (<s> Today is the, first)
  - …

Data for LM is cheap

Data for LM is cheap

Data for LM is cheap

Text

Text is abundant

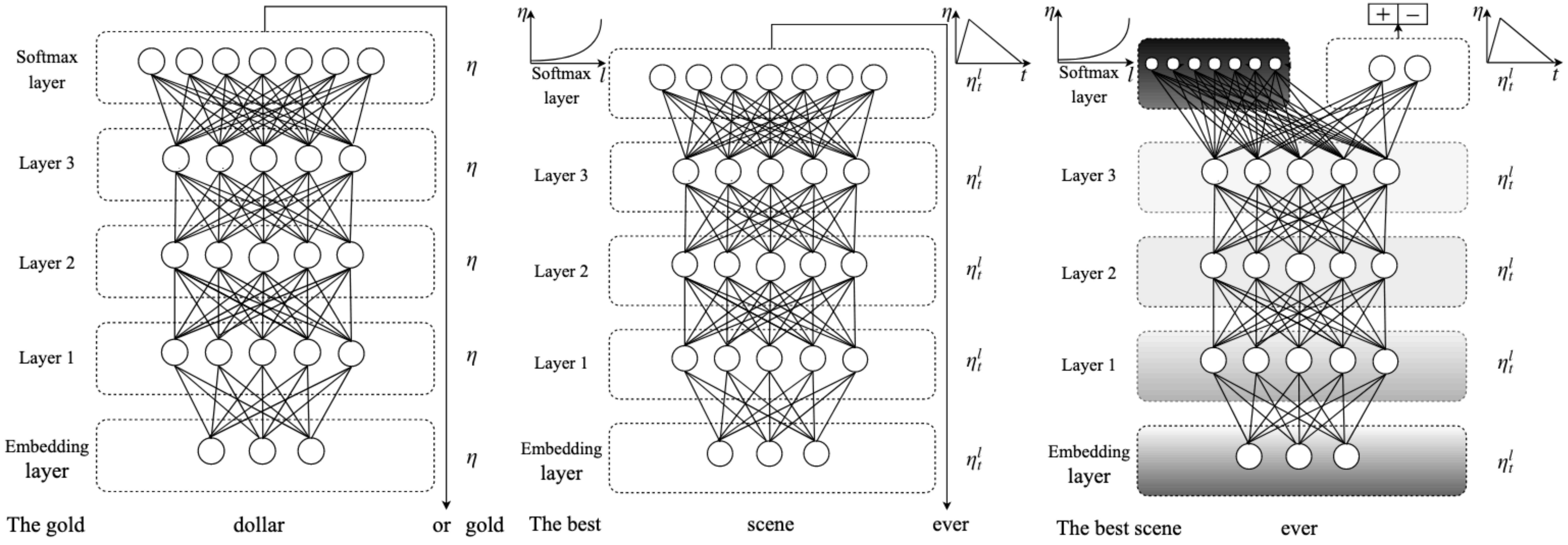
- News sites (e.g. Google 1B)
- Wikipedia (e.g. WikiText103)
- Reddit
- ….
- General web crawling:
  - https://commoncrawl.org/

The Revolution will not be [Annotated]

Yann LeCun

https://twitter.com/rgblong/status/916062474545319938?lang=en

ULMFiT



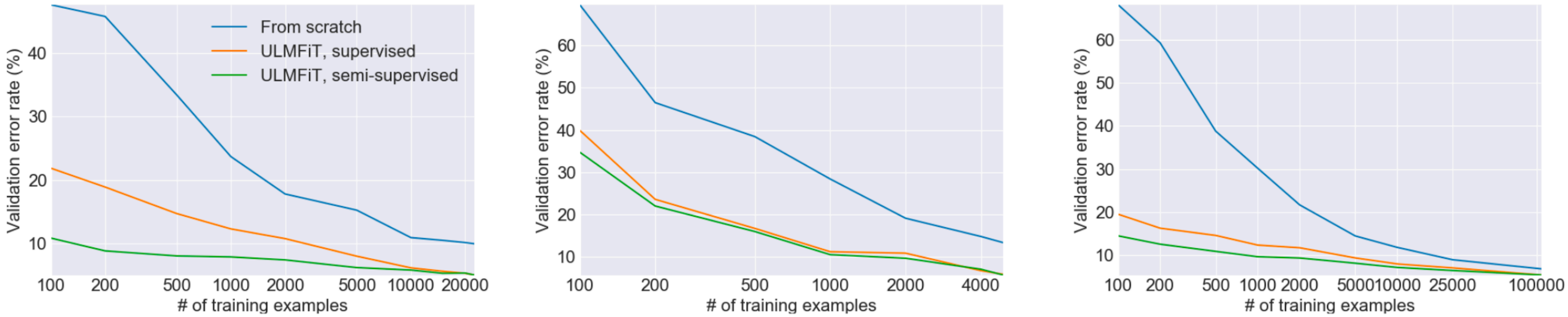
(a) LM pre-training (b) LM fine-tuning (c) Classifier fine-tuning

Universal Language Model Fine-tuning for Text Classification (ACL '18)

ULMFiT

	Model	Test		Model	Test
IMDb	CoVe (McCann et al., 2017)	8.2	TREC-6	CoVe (McCann et al., 2017)	4.2
	oh-LSTM (Johnson and Zhang, 2016)	5.9		TBCNN (Mou et al., 2015)	4.0
	Virtual (Miyato et al., 2016)	5.9		LSTM-CNN (Zhou et al., 2016)	3.9
	ULMFiT (ours)	**4.6**		ULMFiT (ours)	**3.6**

ULMFiT


From scratch
ULMFiT, supervised
ULMFiT, semi-supervised
Validation error rate (%)
# of training examples
100
200
500
1000
2000
5000
10000
20000
4000
25000
100000
10
20
30
40
50
60

Deep Contextualized Word Representations

Peters et. al (2018)

Deep Contextualized Word Representations

Peters et. al (2018)

- NAACL 2018 Best Paper Award

Deep Contextualized Word Representations

Peters et. al (2018)

- NAACL 2018 Best Paper Award
- **E**mbeddings from **L**anguage **Mo**dels (ELMo)
  - [aka the OG NLP Muppet]

Deep Contextualized Word Representations

Peters et. al (2018)

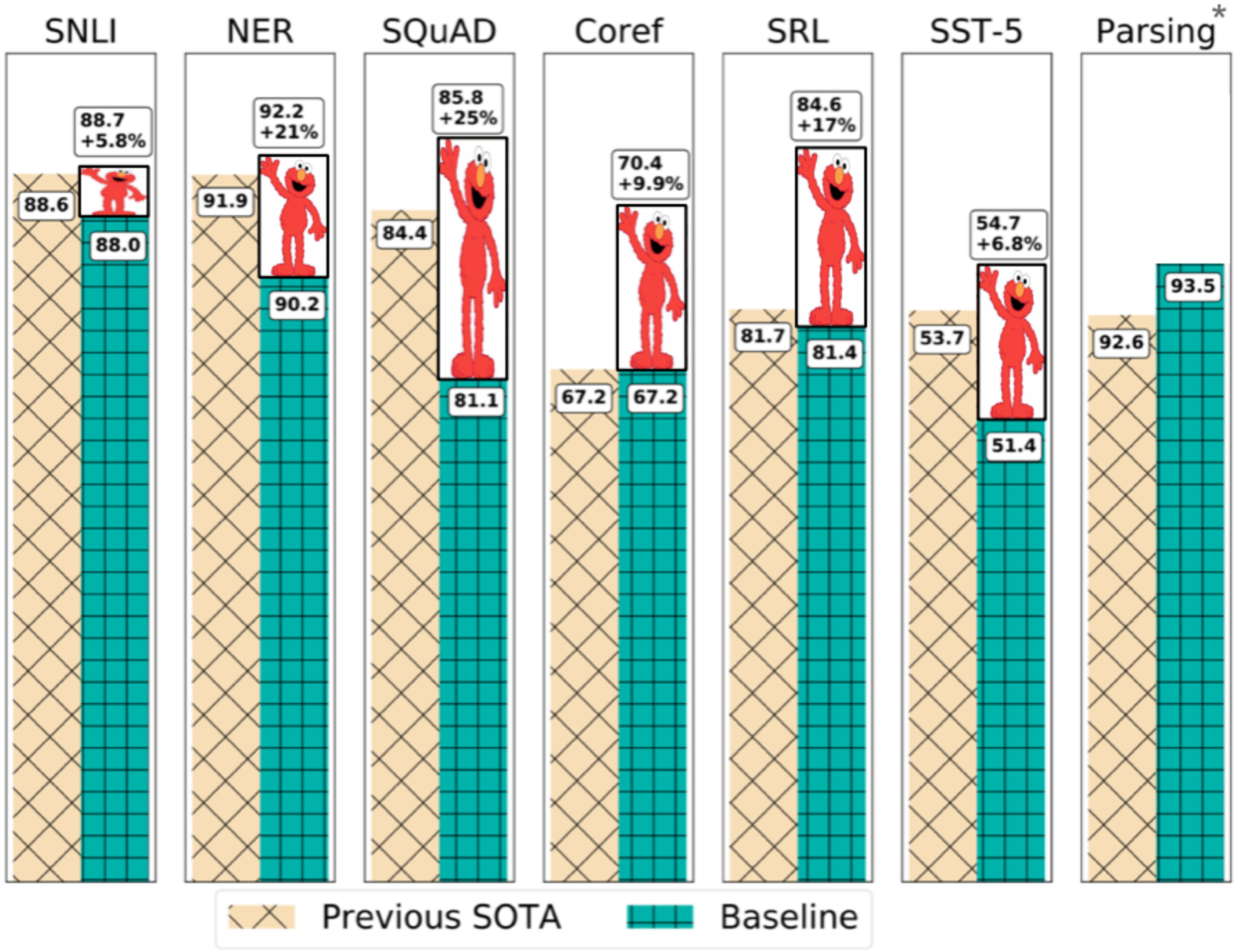
- Comparison to GloVe:

	Source	Nearest Neighbors
GloVe	play	playing, game, games, played, players, plays, player, Play, football, multiplayer
biLM	Chico Ruiz made a spectacular **play** on Alusik's grounder…	Kieffer, the only junior in the group, was commended for his ability to hit in the clutch, as well as his all-round excellent **play**.
	Olivia De Havilland signed to do a Broadway **play** for Garson…	…they were actors who had been handed fat roles in a successful **play**, and had talent enough to fill the roles competently, with nice understatement.

Deep Contextualized Word Representations

[Peters et. al (2018)](#)

- Used in place of other embeddings on multiple tasks:



*Kitaev and Klein, ACL 2018 (see also Joshi et al., ACL 2018)

SQuAD = Stanford Question Answering Dataset
SNLI = Stanford Natural Language Inference Corpus
SST-5 = Stanford Sentiment Treebank

figure: Matthew Peters

BERT

Bidirectional Encoder Representations from Transformers

Devlin et al 2019

Initial Results

System	MNLI-(m/mm)	QQP	QNLI	SST-2	CoLA	STS-B	MRPC	RTE	**Average**
	392k	363k	108k	67k	8.5k	5.7k	3.5k	2.5k	-
Pre-OpenAI SOTA	80.6/80.1	66.1	82.3	93.2	35.0	81.0	86.0	61.7	74.0
BiLSTM+ELMo+Attn	76.4/76.1	64.8	79.8	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	87.4	91.3	45.4	80.0	82.3	56.0	75.1
$\text{BERT}_{\text{BASE}}$	84.6/83.4	71.2	90.5	93.5	52.1	85.8	88.9	66.4	79.6
$\text{BERT}_{\text{LARGE}}$	**86.7/85.9**	**72.1**	**92.7**	**94.9**	**60.5**	**86.5**	**89.3**	**70.1**	**82.1**

Major Application

Google

The Keyword   Latest Stories   Product Updates   Company News

SEARCH

Understanding searches better than ever before

Pandu Nayak
Google Fellow and Vice President, Search

Published Oct 25, 2019

If there's one thing I've learned over the 15 years working on Google Search, it's that people's curiosity is endless. We see billions of searches every day, and 15 percent of those queries are ones we haven't seen before--so we've built ways to return results for queries we can't anticipate.

https://www.blog.google/products/search/search-language-understanding-bert/

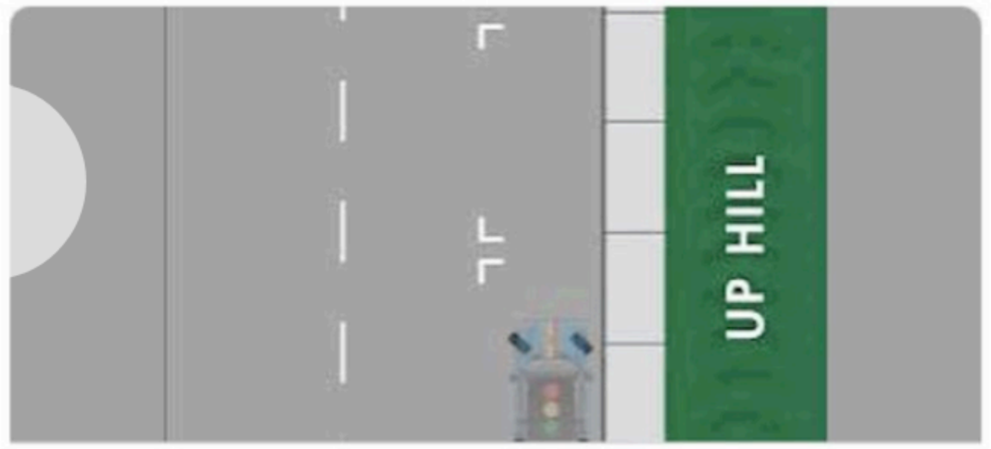
Major Application

parking on a hill with no curb

BEFORE

9:00

google.com



Parking on a Hill. Uphill: When headed uphill at a **curb**, turn the front wheels away from the **curb** and let your vehicle roll backwards slowly until the rear part of the front wheel rests against the **curb** using it as a block. Downhill: When you stop your car headed downhill, turn your front wheels

AFTER

9:00

google.com

For either uphill or downhill **parking**, if there is no **curb**, turn the wheels toward the side of the road so the car will roll away from the center of the road if the brakes fail. When you park on a sloping driveway, turn the wheels so that the car will not roll into the

Pre-trained Neural Models Everywhere

GLUE SuperGLUE Paper </> Code Tasks Leaderboard FAQ Diagnostics Submit

Rank	Name	Model	URL	Score	CoLA	SST-2	MRPC	STS-B	QQP	MNLI-m	MNLI-mm	QNLI	RTE	WNLI	AX
1	ERNIE Team - Baidu	ERNIE		90.2	72.2	97.5	93.0/90.7	92.9/92.5	75.2/90.8	91.2	90.6	98.0	90.9	94.5	49.4
+ 2	王玮	ALICE v2 large ensemble (Alibaba DAMO NLP)		90.1	73.2	97.1	93.9/91.9	93.0/92.5	74.8/91.0	90.8	90.6	99.2	87.4	94.5	48.7
3	Microsoft D365 AI & MSR AI & GATECH	MT-DNN-SMART		89.9	69.5	97.5	93.7/91.6	92.9/92.5	73.9/90.2	91.0	90.8	99.2	89.7	94.5	50.2
4	T5 Team - Google	T5		89.7	70.8	97.1	91.9/89.2	92.5/92.1	74.6/90.4	92.0	91.7	96.7	92.5	93.2	53.1
5	XLNet Team	XLNet (ensemble)		89.5	70.2	97.1	92.9/90.5	93.0/92.6	74.7/90.4	90.9	90.9	99.0	88.5	92.5	48.4
6	ALBERT-Team Google Language	ALBERT (Ensemble)		89.4	69.1	97.1	93.4/91.2	92.5/92.0	74.2/90.5	91.3	91.0	99.2	89.2	91.8	50.2
7	Microsoft D365 AI & UMD	FreeLB-RoBERTa (ensemble)		88.8	68.0	96.8	93.1/90.8	92.4/92.2	74.8/90.3	91.1	90.7	98.8	88.7	89.0	50.1
8	Facebook AI	RoBERTa		88.5	67.8	96.7	92.3/89.8	92.2/91.9	74.3/90.2	90.8	90.2	98.9	88.2	89.0	48.7
9	Junjie Yang	HIRE-RoBERTa		88.3	68.6	97.1	93.0/90.7	92.4/92.0	74.3/90.2	90.7	90.4	95.5	87.9	89.0	49.3
+ 10	Microsoft D365 AI & MSR AI	MT-DNN-ensemble		87.6	68.4	96.5	92.7/90.3	91.1/90.7	73.7/89.9	87.9	87.4	96.0	86.3	89.0	42.8
11	GLUE Human Baselines	GLUE Human Baselines		87.1	66.4	97.8	86.3/80.8	92.7/92.6	59.5/80.4	92.0	92.8	91.2	93.6	95.9	-

[General Language Understanding Evaluation (GLUE)]() / [SuperGLUE]()

Sidebar: Word Embeddings

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- Aren't word embeddings like word2vec and GloVe examples of transfer learning?
  - Yes: get linguistic representations from raw text to use in downstream tasks
  - No: not intended to be used as *general-purpose* representations

Sidebar: Word Embeddings

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- One distinction:
  - *Global* representations:
    - word2vec, GloVe: *one* vector for each word *type* (e.g. ‘play’)
  - *Contextual* representations (from LMs):
    - Representation of word in context, not independently

Sidebar: Word Embeddings

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  - *Contextual* representations (from LMs):
    - Representation of word in context, not independently
- Another:
  - *Shallow* (global) vs. *Deep* (contextual) pre-training

Global Embeddings: Models

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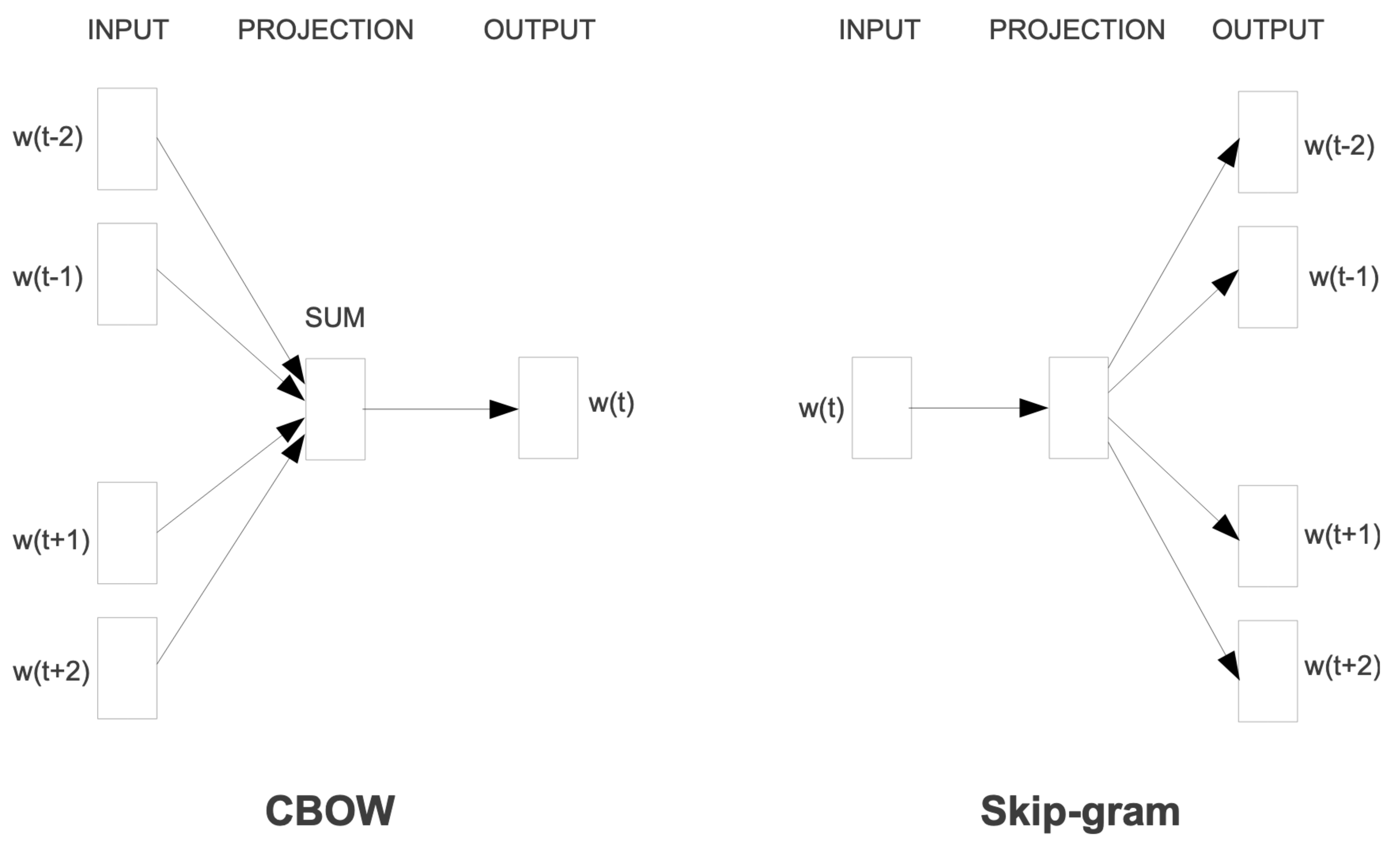
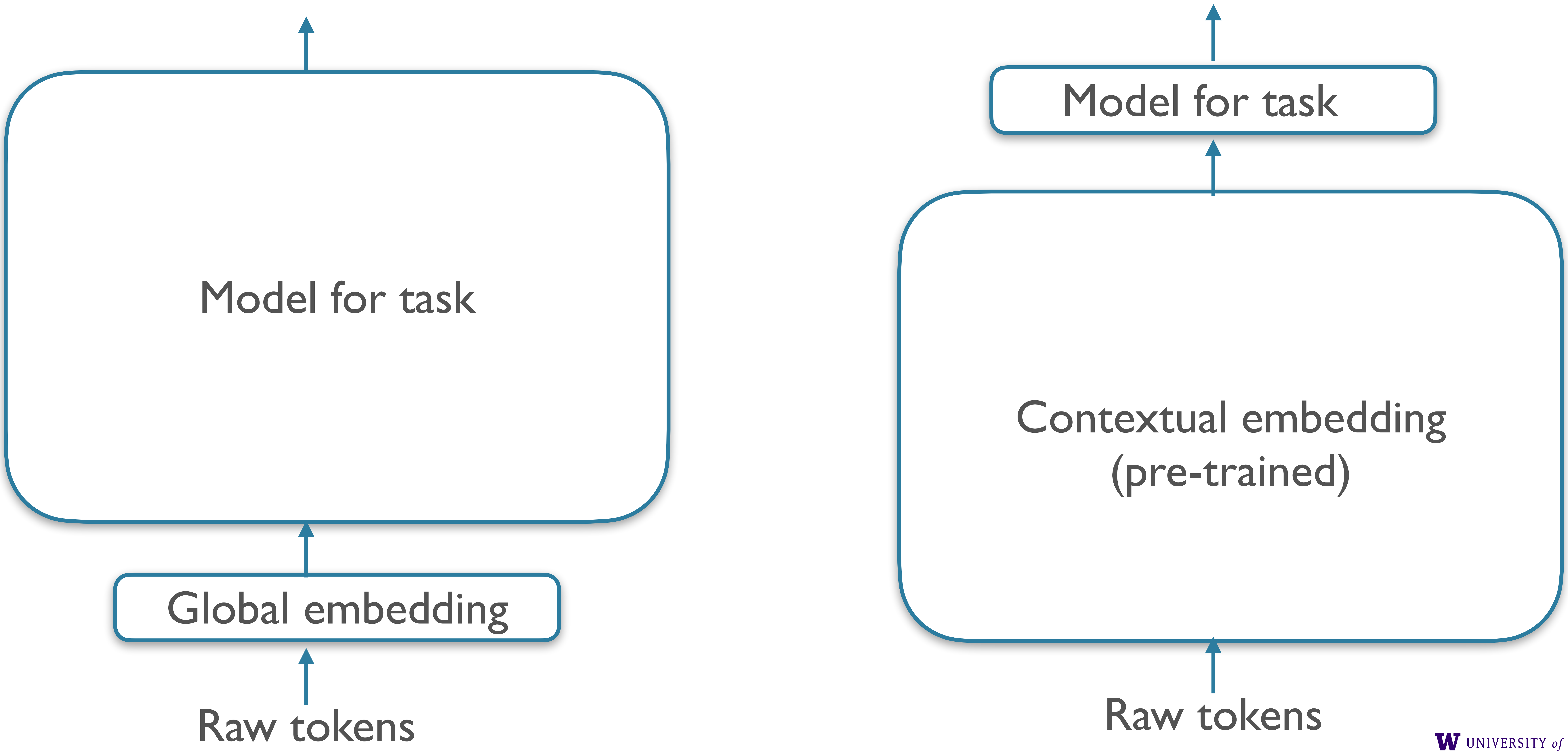


Mikolov et al 2013a (the OG `word2vec` paper)

Shallow vs Deep Pre-training



NLP’s “Clever Hans Moment”

The Gradient

ME EDITOR'S NOTE OVERVIEWS PERSPECTIVES ABOUT SUBSCRIBE

Clever Hans

BERT

NLP's Clever Hans Moment has Arrived

26.AUG.2019

link

Clever Hans

- Early 1900s, a horse trained by his owner to do:
  - Addition
  - Division
  - Multiplication
  - Tell time
  - Read German
  - …

- Wow! Hans is really smart!

Clever Hans Effect

Clever Hans Effect

- Upon closer examination / experimentation…

Clever Hans Effect

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- Hans' success:

Clever Hans Effect

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- Hans' success:
  - 89% when questioner knows answer

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- Further experiments: as Hans' taps got closer to correct answer, facial tension in questioner increased

Clever Hans Effect

- Upon closer examination / experimentation…
- Hans' success:
  - 89% when questioner knows answer
  - 6% when questioner doesn't know answer
- Further experiments: as Hans' taps got closer to correct answer, facial tension in questioner increased
- Hans didn't solve the task but exploited *a spuriously correlated cue*

Central question

- Do BERT et al’s major successes at solving NLP tasks show that we have achieved robust natural language understanding in machines?

- Or: are we seeing a “Clever BERT” phenomenon?

Right for the Wrong Reasons: Diagnosing Syntactic Heuristics in Natural Language Inference

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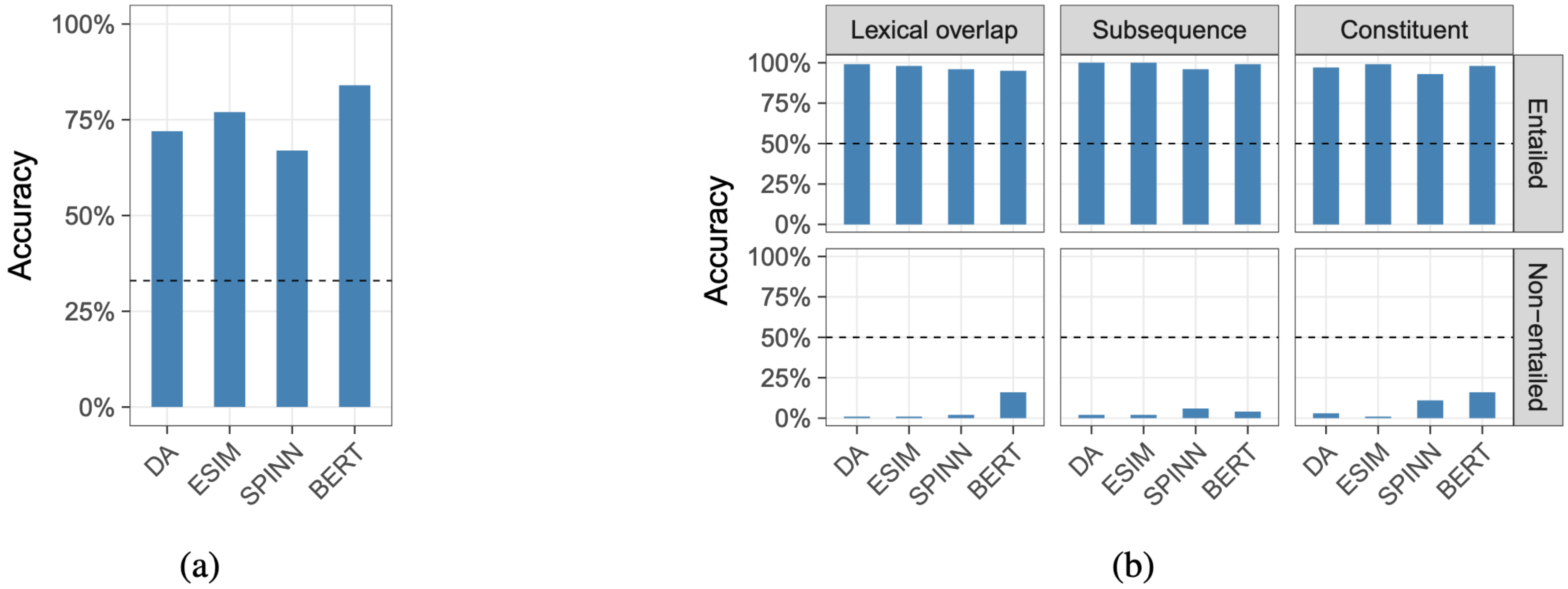
McCoy et al 2019

Heuristic	Premise	Hypothesis	Label
Lexical overlap heuristic	The banker near the judge saw the actor.	The banker saw the actor.	E
	The lawyer was advised by the actor.	The actor advised the lawyer.	E
	The doctors visited the lawyer.	The lawyer visited the doctors.	N
	The judge by the actor stopped the banker.	The banker stopped the actor.	N
Subsequence heuristic	The artist and the student called the judge.	The student called the judge.	E
	Angry tourists helped the lawyer.	Tourists helped the lawyer.	E
	The judges heard the actors resigned.	The judges heard the actors.	N
	The senator near the lawyer danced.	The lawyer danced.	N
Constituent heuristic	Before the actor slept, the senator ran.	The actor slept.	E
	The lawyer knew that the judges shouted.	The judges shouted.	E
	If the actor slept, the judge saw the artist.	The actor slept.	N
	The lawyers resigned, or the artist slept.	The artist slept.	N

Results



(performance improves if fine-tuned on this challenge set)

Probing Neural Network Comprehension of Natural Language Arguments

Timothy Niven and **Hung-Yu Kao**

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Abstract

We are surprised to find that BERT's peak performance of 77% on the Argument Reasoning Comprehension Task reaches just three points below the average untrained human baseline. However, we show that this result is entirely accounted for by exploitation of spurious statistical cues in the dataset. We analyze the nature of these cues and demonstrate that a range of models all exploit them. This analysis informs the construction of an adversarial dataset on which all models achieve random accuracy. Our adversarial dataset provides a

Claim	Google is not a harmful monopoly
Reason	People can choose not to use Google
Warrant	Other search engines don't redirect to Google
Alternative	All other search engines redirect to Google

Reason (and since) **Warrant** $\rightarrow$ **Claim**
Reason (but since) **Alternative** $\rightarrow \neg$ **Claim**

Figure 1: An example of a data point from the ARCT test set and how it should be read. The inference from R and A to $\neg C$ is by design.

The Argument Reasoning Comprehension Task (ARCT) (Habernal et al., 2018a) defers the prob-

link

Recent Analysis Explosion

- E.g. BlackboxNLP workshop [2018, 2019, 2020, 2021]
- New "Interpretability and Analysis" track at *CL conferences

Why care?

- Effects of learning what neural language models understand:
  - Engineering: can help build better language technologies via improved models, data, training protocols, …
    - Trust, critical applications
  - Theoretical: can help us understand biases in different architectures (e.g. LSTMs vs Transformers), similarities to human learning biases
    - Which linguistic features / properties are *learnable* from raw text alone?
  - Ethical: e.g. do some models reflect problematic social biases more than others?

Stretch Break!

Course Overview / Logistics

Large Scale

- Motivating question: what do neural language models understand about natural language?
  - Focus on *meaning*, where much of the literature has focused on *syntax*
- A *research seminar*: in groups, you will carry out and execute a novel analysis project.
  - Think of it as a proto-conference-paper, or the seed of a conference paper.

Course structure

- First half: learning about the tools and techniques required
  - Wk 2: language models
    [architectures, tasks, data, …]
  - Wk 3: analysis methods
    [visualization, probing classifiers, artificial data, …]
  - Wk 4: resources / datasets
  - Wk 5: technical resources / writing tips
- Be active! Reading, participating, planning ahead

Course structure

- Second half: *presentations*
  - Each group will give one “special topic” presentation and lead a discussion, e.g.:
    - reading a paper or two on a topic related to your final project
    - explaining a method you are using in project, issues, etc.
  - ~~Final week: project presentation festival!~~
    - ~~“Mini conference”, incl. reception~~
  - **NO CLASS ON MAY 18**

Evaluation

- Proposal: 10%
- Special topic presentation: 30%
- Final paper: 50%
- Participation: 10%

Reading List

- Semi-comprehensive list of recent papers on website
  - Key-words for sorting
  - NB: also outdated; impossible to keep up with the entire literature
- Browse, get ideas/inspiration
- Deep dive on a few later

Examples of Final Paper Titles

- Probing for Numerical Understanding in Transformer-Based Language Models
- Investigating positional information in the Transformer
- Discernment of Implicature in Natural language Inference:New Data and Classifier Implementations
- Exploring influence of grammatical gender on gender bias in transformer-based multilingual language models
- Probing for Visual Knowledge in Large Language Models

Examples of Final Paper Titles

- Mighty Morpho-Tagging Models from BERT
- Oscar the GROUCH: Graphical Representations and Observations for Understanding Classification of Hate
- Can You Get it Right Consistently? Probing BERT’s Robustness in Natural Language Understanding
- Probing Language Models for Understanding of Temporal Expressions
- Analyzing Individual Neurons in Mono and Multilingual BERT Models

Group Formation (HW1)

Three Tasks

- Form groups (more next)
- Set up repository
  - GitHub, GitLab, patas Git server …
  - Make it private for now!
  - Don’t put private or sensitive data in the repo! (incl LDC corpora)
- Add ACL paper template to repository
  - https://github.com/acl-org/acl-style-files
  - Format for final paper

Groups

- There will be *eight* groups
  - Sized 2-4 people
- Unified grade
- Group decides how to divide work, but reports who did what at the end.
- Aim to diversify talents / interests in the group.
  - Experimental design
  - Data work
  - Implementation
  - Experiment running / analyzing
  - Writing
  - Speaking (presentations)

Communication

- CLMS Student Slack
  - Useful, since a majority of students in this seminar are on it already
  - Self-organize (575 channel?), based on interests, background competences, etc
  - For students not on it yet:
    - Canvas thread for requesting access
    - CLMS students: please add ASAP

- For general / non-group discussions, still use Canvas discussions.
- NB: I am not on that Slack (nor are other faculty)

Registering Groups

- List your groups here:
  - https://docs.google.com/spreadsheets/d/18ldxVhTIQ2q5-vrR409DhvsGP2nn6-ajuPtgnDa7hUg/edit#gid=0

- On Canvas, upload “readme.pdf” with:
  - Group #, screenshot of repository

Thanks! Looking forward to a great quarter!