Oct 16, 2019

Industrialized Capsule Network for Text Analytics

http://bit.ly/aiconf2019

publicis sapient

About the Speaker

Dr. Vijay Agneeswaran

Head of Data Science, **Walmart Labs**

MS (Research) & PhD , **IIT Madras**

Post doctoral research fellowship, **LSIR Labs**

Professional member : **ACM, IEEE (Senior)**

4 Full US Patents and multiple publications (including **IEEE** journals)

Regular Speaker @ **O'Reilly Strata & AI conference**

About the Speaker

Abhishek Kumar

Senior Data Scientist @ **Publicis Sapient**

Masters from **University of California, Berkeley**

Google Developer Expert – (Machine Learning)

Speaker @ **O'Reilly Strata & AI conference**

Pluralsight Author

Recognizing Trends in Social Media

Source : https://www.cbsnews.com/news/metoo-reaches-85-countries-with-1-7-million-tweets/

How Effective are Political Campaigns?
Feedback for Various Policy Decisions

Call Center / Customer Support Performance

Supervised Learning Problems

1. Audience Segment on social platforms
2. Text categorization (Articles, News , Blogs)
3. Tagging (Queries)
4. Spam Detection
5. Reviews Classification

Text Analytics and NLP - Background

Text Analytics and NLP

Syntactic Layer	Semantic Layer	Pragmatic Layer
Microtext Normalization	Word Sense Disambiguation	Personality Recognition
Sentence Boundary Disambiguation	Concept Extraction	Metaphor Understanding
POS Tagging	NER (Named Entity Recognition)	Aspect Extraction
Text Chunking, Lemmatization	Subjectivity Detection (e.g Sentiment)	Polarity Detection

Common Models for NLP: History

First Order Logic (FOL)

All birds fly. Penguins do not fly. Penguins are birds?

Production Rules

- Recognize, resolve conflict, act – cycles.
- Scalability issues.

Ontology Web Language (OWL)

- Resource Definition Format (RDF) for subject-predicate-object models.
- Suitable more for declarative knowledge, harder to express subjectivity.

Networks – Bayesian, for example.

- Prior knowledge + evidence of likelihood of events.
- Limited expressiveness + difficult to determine probability of each variable.

Semantic networks

- Graphs of concepts and how they are related.
- Generalization, specialization in definitional networks, propositions in assertional networks.
- Minsky's theory of human knowledge – basis of common-sense knowledge basis for NLP tasks

Machine Learning & Deep Learning for NLP

Machine Learning	Deep Learning
• assigning labels to words • extract rich set of hand-crafted features • task dependent features • semantic role labeling task may require complex features	• Avoid too much pre-processing • Avoid hand-crafted feature generation • Avoid task specific features • Better generalization • features are learnt by the deep layers of the network taking as input only the sentences

Overlapping NLP Curves

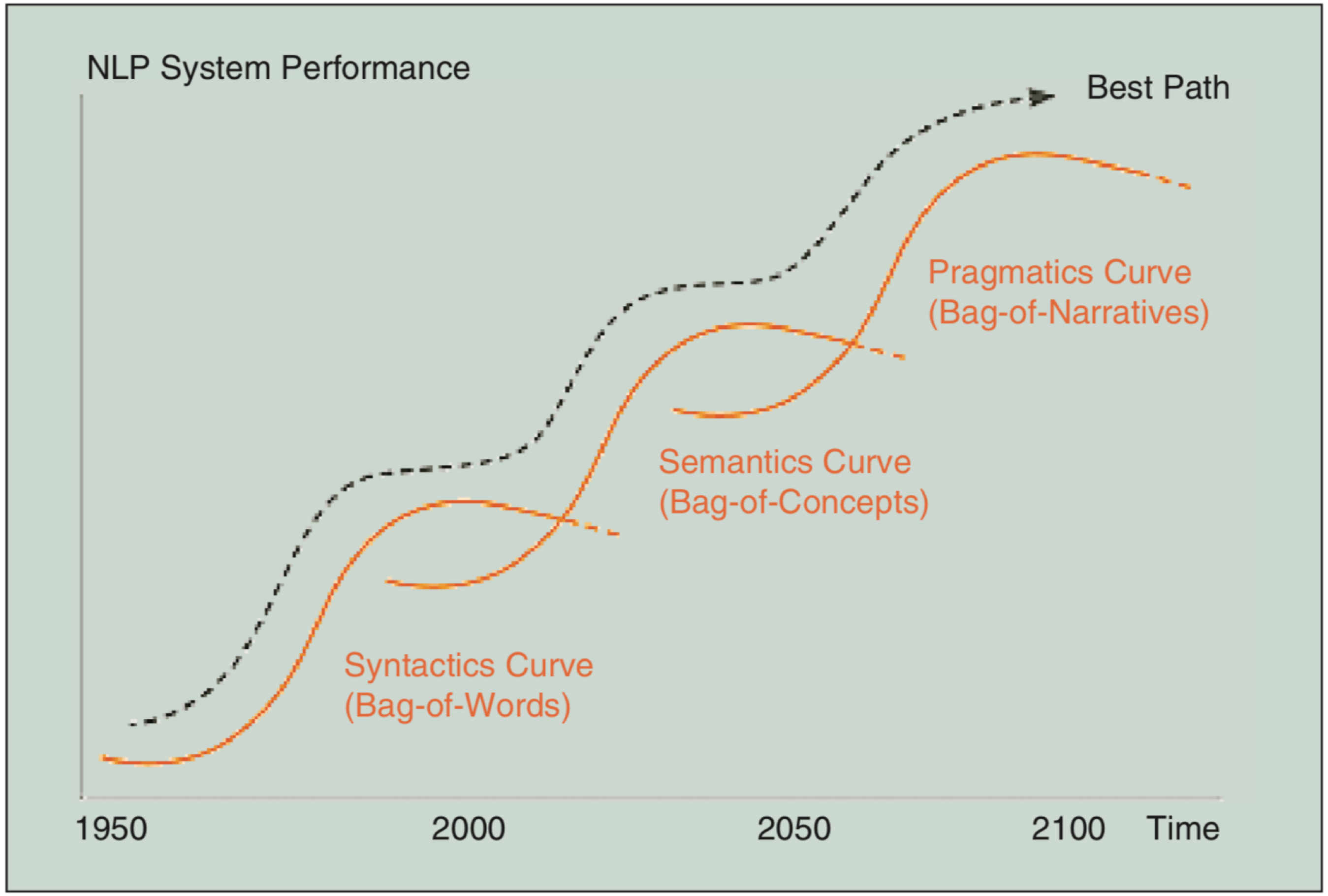


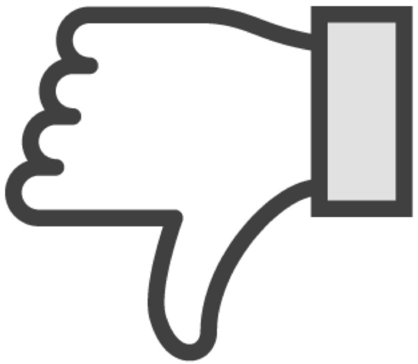
FIGURE 1 Envisioned evolution of NLP research through three different eras or curves.

Erik Cambria and Bebo White. 2014. Jumping NLP Curves: A Review of Natural Language Processing Research [Review Article]. Comp. Intell. Mag.9, 2 (May 2014), 48-57. DOI: https://doi.org/10.1109/MCI.2014.2307227

Text Modeling

IMBD Review

A big disappointment for what was touted as an incredible film. Incredibly bad. Very pretentious. It would be nice if just once someone would create a high profile role



Bag-Of-Words

Individual Words are Important

IMBD Review

A big disappointment for what was touted as an incredible film. Incredibly bad. Very pretentious. It would be nice if just once someone would create a high profile role

Word	Count	TF-IDF
Big	..	..
Disappointment	..	..
Incredible	..	..
Bad	..	..
Pretentious	..	..
Nice	..	..

Missing Context

Word Embedding

Use corpus to use context to create dense word representation

IMBD Review

A big disappointment for what was touted as an incredible film. Incredibly bad. Very pretentious. It would be nice if just once someone would create a high profile role

Word	Word2 Vec	FastText	Glove
Big	..	..	
Disappointment	..	..	
Incredible	..	..	
Bad	..	..	
Pretentious	..	..	
Nice	..	..	

Only Word Level.. But how to model beyond "Word Meaning"

Text as Sequence Modeling Through Deep learning

Modeling spatial Relationship

IMBD Review

A big disappointment for what was touted as an incredible film. Incredibly bad. Very pretentious. It would be nice if just once someone would create a high profile role

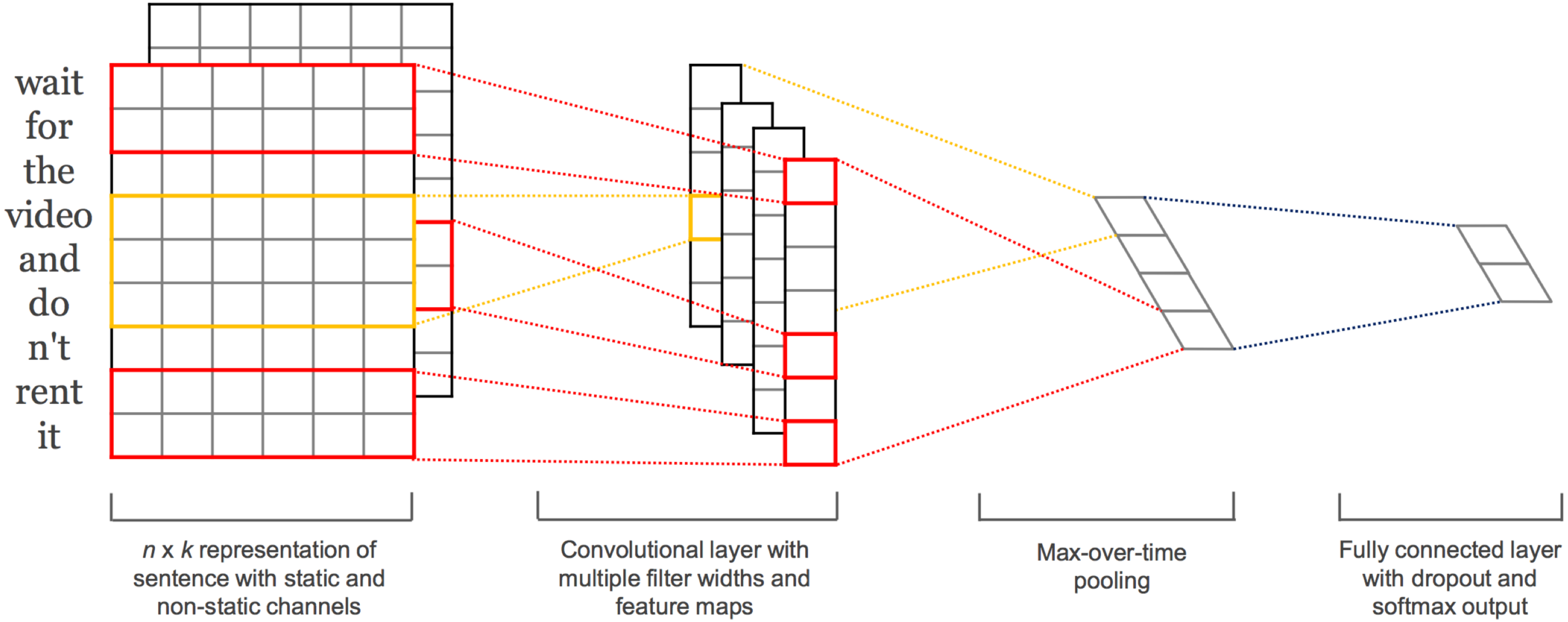
Text as Sequence Modeling Through Deep learning

Use Spatial Patterns

CNN, LSTM Approaches (use window of vector sequences)

Convolution Neural Networks

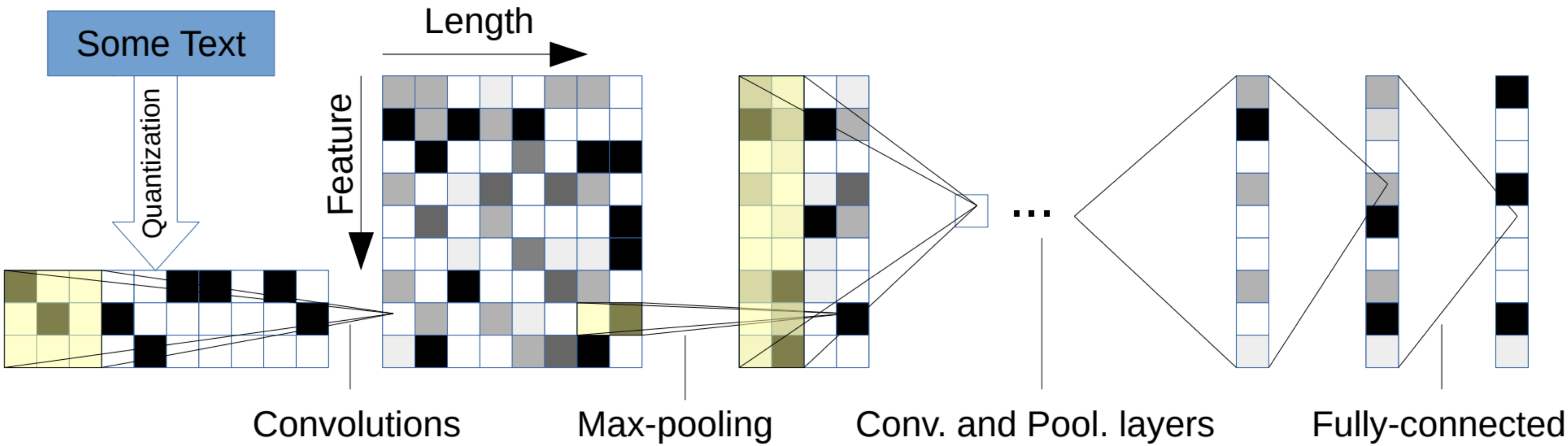
Convolution Neural Networks For Sentence Classification, Yoon Kim (2014)



https://www.aclweb.org/anthology/D14-1181.pdf

Convolution Neural Networks

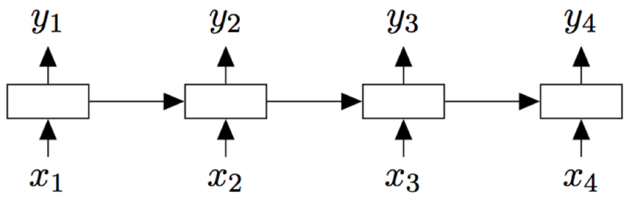
Character-Level Convolution Networks For Text Classification, Zhang et.al. (2015)



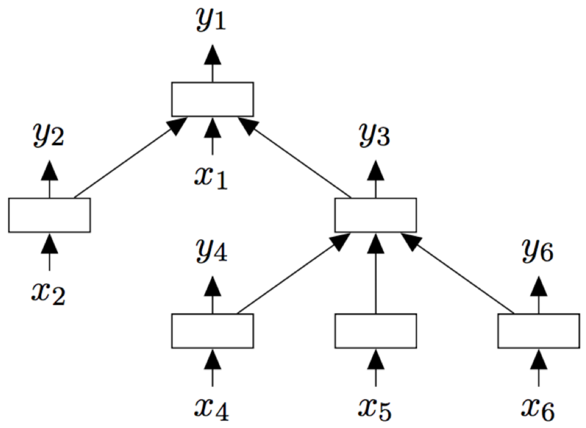
https://arxiv.org/pdf/1509.01626.pdf

LSTM (Long Short Term Memory)

Improved Semantic Representations From Tree-Structured Long Short-Term Memory Networks, Tai et.al 2015



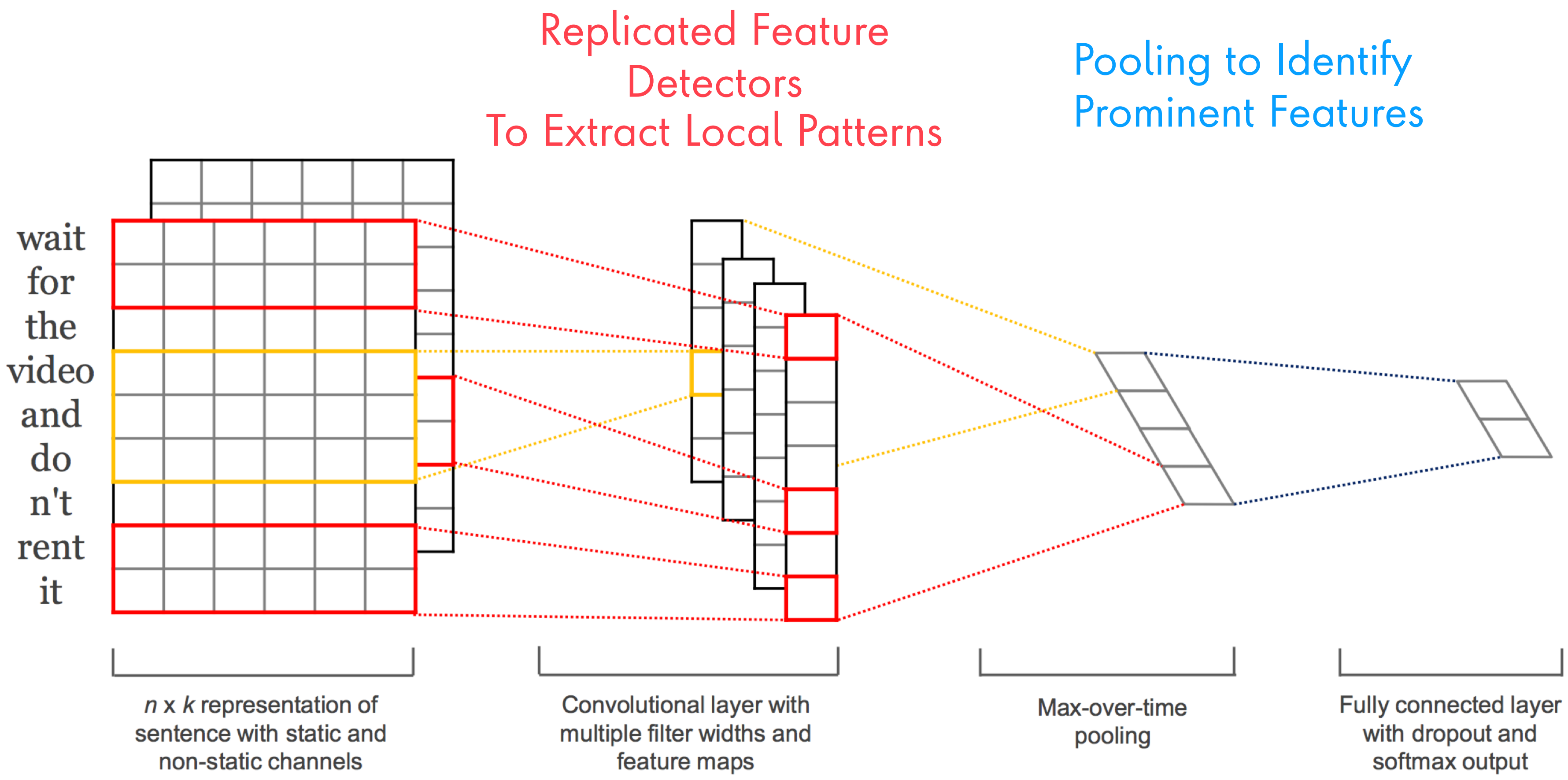
Chain-structured LSTM



Tree-structured LSTM

https://arxiv.org/pdf/1503.00075.pdf

Neural Network Approach



Neural Network Approach

CNNs can deal with translation out of the box, but for robust recognition in the face of all other kinds of transformation (perspective, brightness, local patterns) there are two choices:

kernels with large dimensions and large overlaps, at the cost of exponentially increasing number of parameters to be learned (use Max-Pooling technique)

Or

Increase the size of the labelled training set in a similarly exponential way. (use data-augmentation techniques)

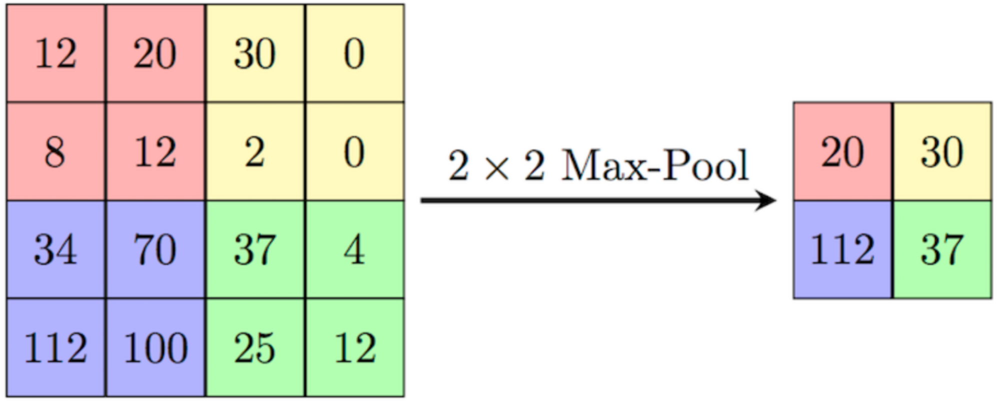
Exponential Inefficiencies

What is the problem with Pooling ?

Most active neurons are passed to next layer

Spatial information is lost

For long text / doc - important concepts will be lost



Dynamic Routing Between Capsules

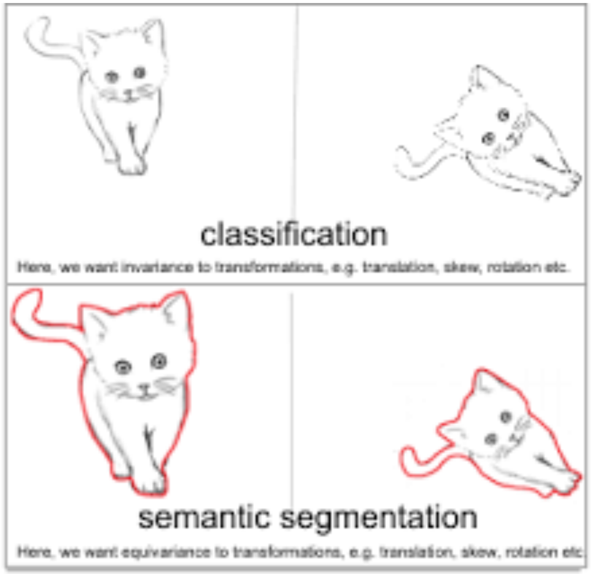
Sara Sabour **Nicholas Frosst**

Geoffrey E. Hinton
Google Brain
Toronto
{sasabour, frosst, geoffhinton}@google.com

Present Spatial Encoding pooling operation used in convolutional neural networks is a big mistake, and the fact that it works so well is a disaster!"

Key Challenges

Solving for invariance not equivariance



CNN unable to disentangle transformations to the image such as rotation, different lighting conditions or different colours etc.

CNN is invariant to input perturbations, while capsule networks is equivariant – output of capsule nets will change when input changes due to perturbations.

How to strike the right balance?

Spatial Sensitive Approaches (e.g. CNN)	Spatial Insensitive Approaches (e.g. Probabilistic Topic Modeling)
Exponential Inefficiencies	Efficient (work on collection and ignore order or local patterns)
Encode rich sequence structure	Can't encode rich sequence structure

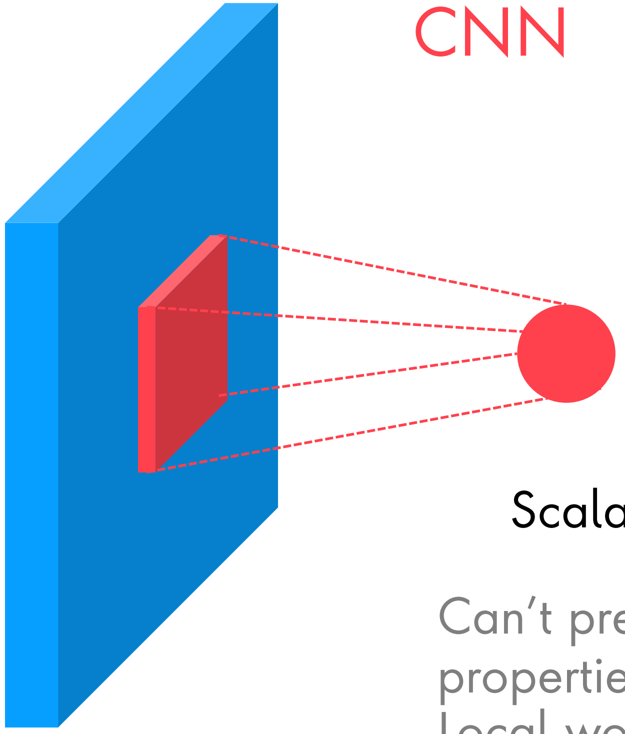
Capsule Networks (for efficiently encode viewpoint invariance)

Background

Capsule Networks

Moving from Scalar to Vector

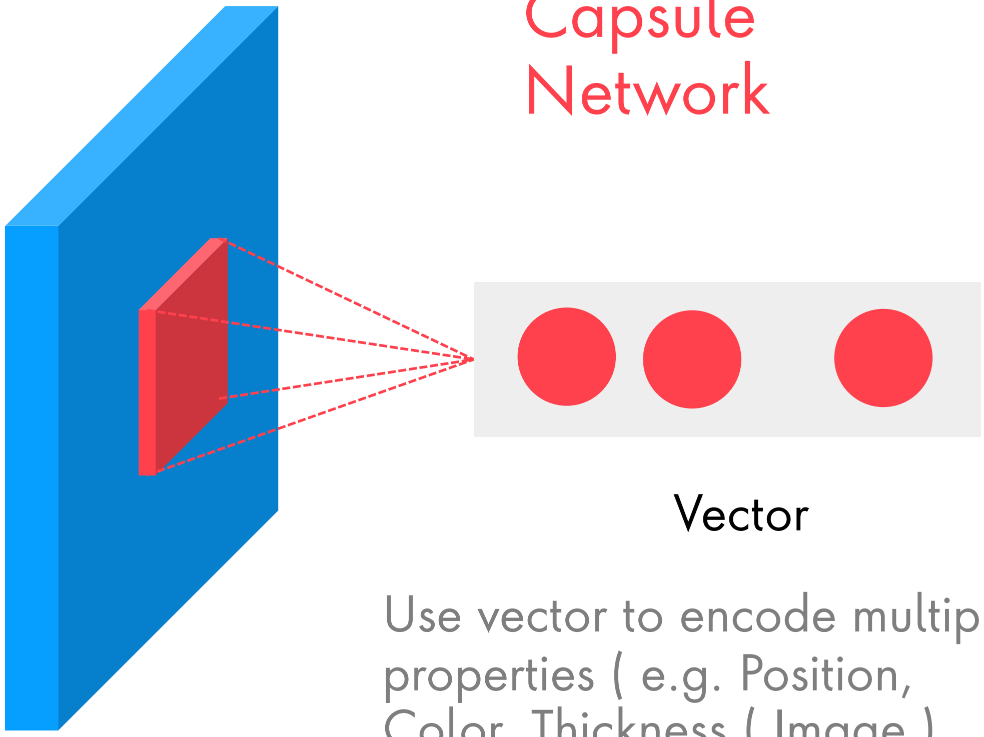
CNN



Scalar

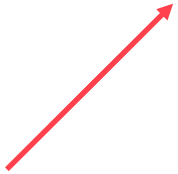
Can't preserve properties of Pixels / Local word Patterns

Capsule Network



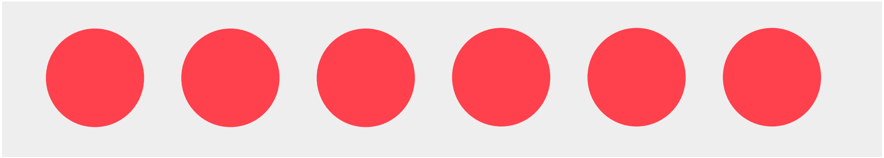
Vector

Use vector to encode multiple properties (e.g. Position, Color, Thickness (Image) Morphology, Semantics (Text)



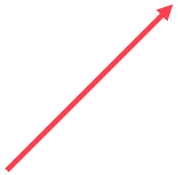
Vector length (norm) is used to encode probability for the output class

Capsule



Use vector to encode multiple properties (e.g. Position, Color, Thickness (Image) Morphology, Semantics (Text)

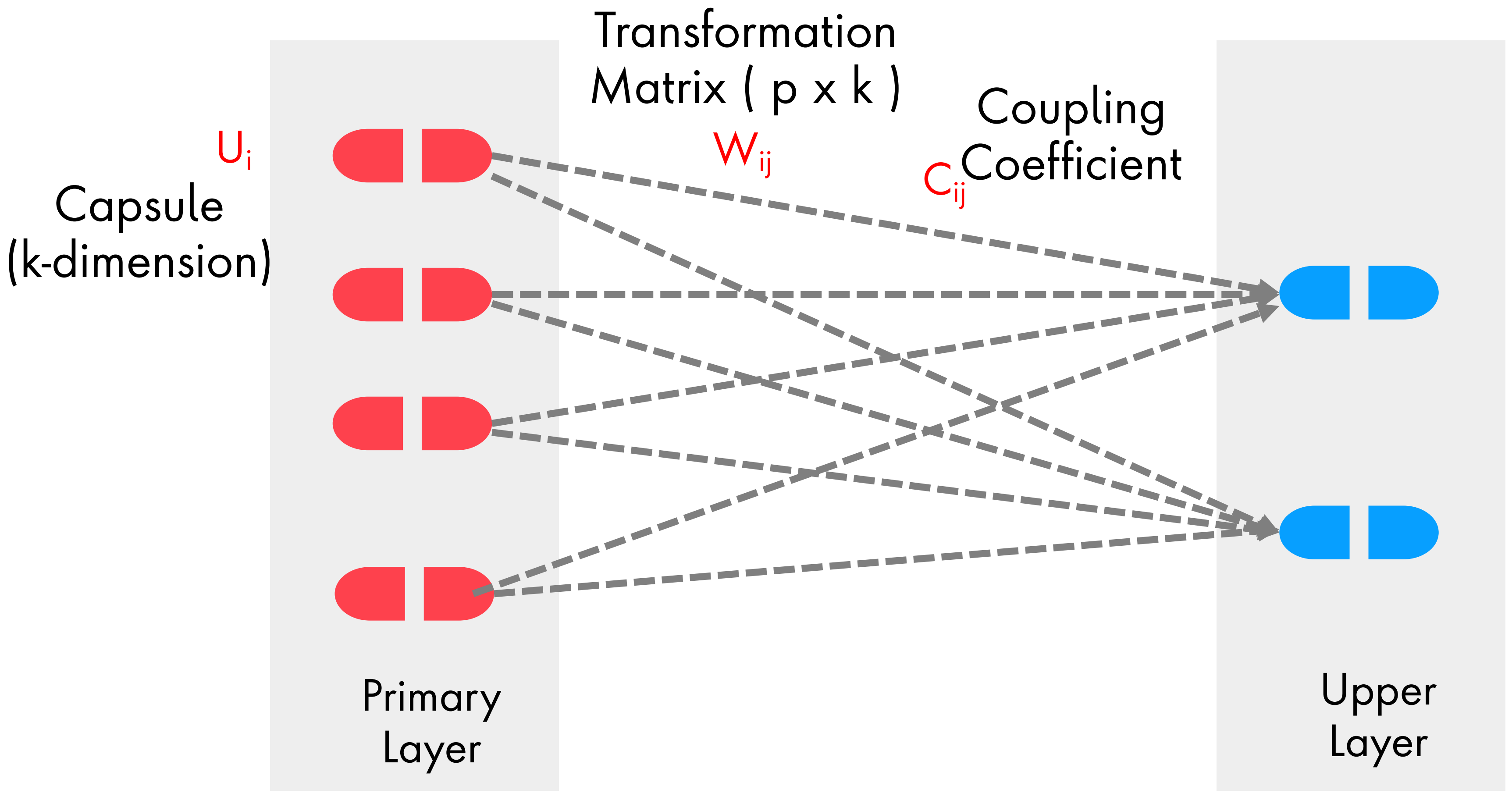
Pose (Instantiation Parameters)



Vector length (norm) is used to encode probability for the output class

Probability

Capsule Output Calculation



c_{ij} measures how likely capsule i may activate capsule j.

1. Apply Transformation on Capsule

$$\hat{u}_{j|i} = W_{ij} u_i$$

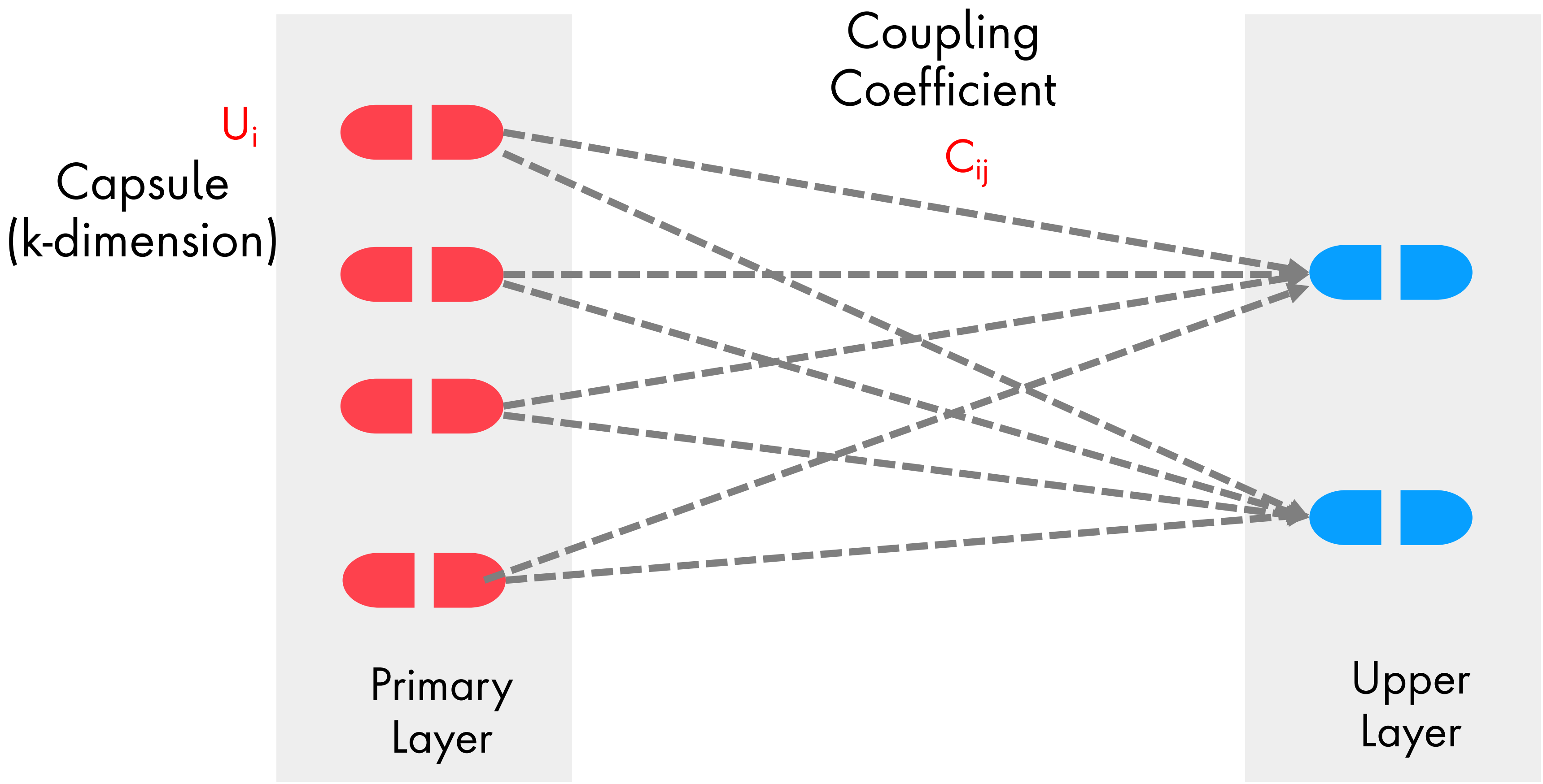
2. Weighted sum using coupling coefficients

$$s_j = \sum_i c_{ij} \hat{u}_{j|i}$$

3. Apply Squashing to have output between 0 and 1

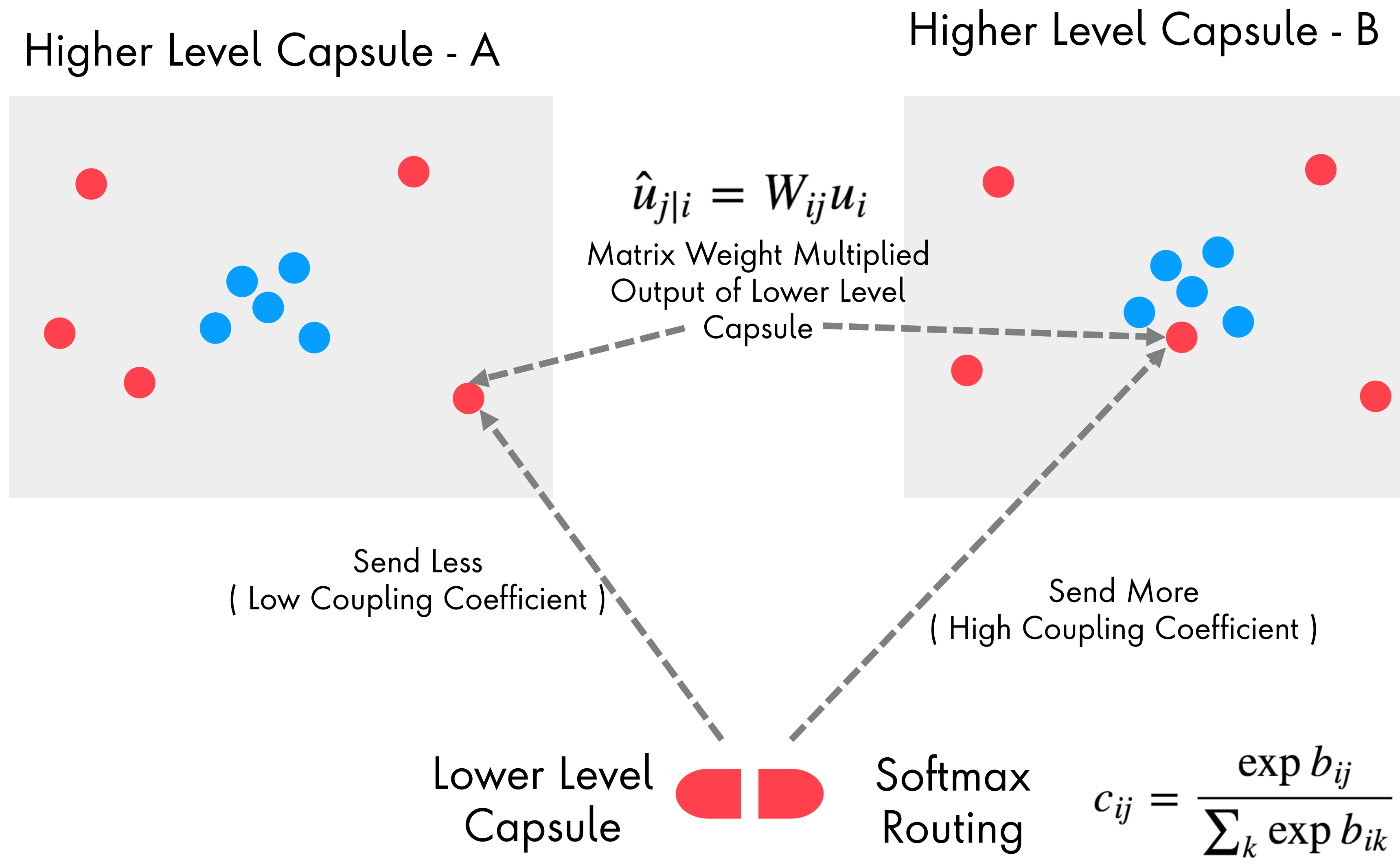
$$v_j = \frac{\|s_j\|^2}{1 + \|s_j\|^2} \frac{s_j}{\|s_j\|}$$

Dynamic Routing



Coupling Coefficients (Scalar weights) determined through "Dynamic Routing" Process

Dynamic Routing (Routing by Agreement)



Dynamic Routing (Routing by Agreement)

1. Calculate Prediction vector (prediction from capsule i to capsule j) $\hat{u}_{j|i} = W_{ij} u_i$

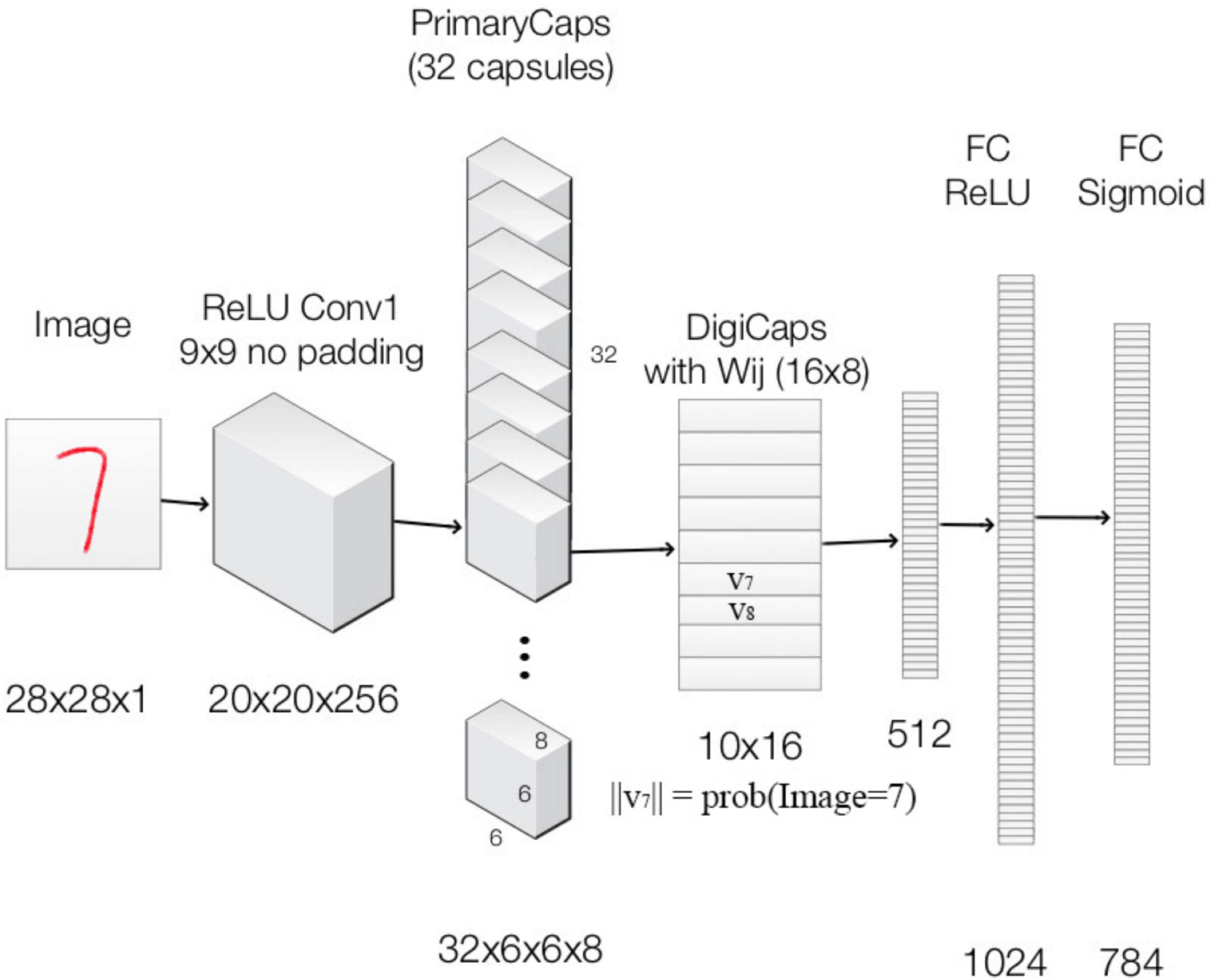
2. Calculate Activity vector v_j (capsule j output) $s_j = \sum_i c_{ij} \hat{u}_{j|i}$ $\quad v_j = \frac{\|s_j\|^2}{1 + \|s_j\|^2} \frac{s_j}{\|s_j\|}$

3. Check if activity is closer to prediction using dot product $b_{ij} \leftarrow \hat{u}_{j|i} \cdot v_j$

4. Calculate coupling coefficient as sofmax of bij $c_{ij} = \frac{\exp b_{ij}}{\sum_k \exp b_{ik}}$

5. Iteratively update b_{ij} $b_{ij} \leftarrow b_{ij} + \hat{u}_{j|i} \cdot v_j$

Capsule Network Architecture for Image Classification



Able to predict from
different viewpoints

Background

Capsule Networks For Text

Capsule Network For Text

Investigating Capsule Networks with Dynamic Routing for Text Classification

Wei Zhao[1,2], **Jianbo Ye**[3], **Min Yang**[1*], **Zeyang Lei**[4], **Soufei Zhang**[5], **Zhou Zhao**[6]
[1] Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences
[2] Tencent [3] Pennsylvania State University
[4] Graduate School at Shenzhen, Tsinghua University
[5] Nanjing University of Posts and Telecommunications [6] Zhejiang University

https://arxiv.org/pdf/1804.00538.pdf

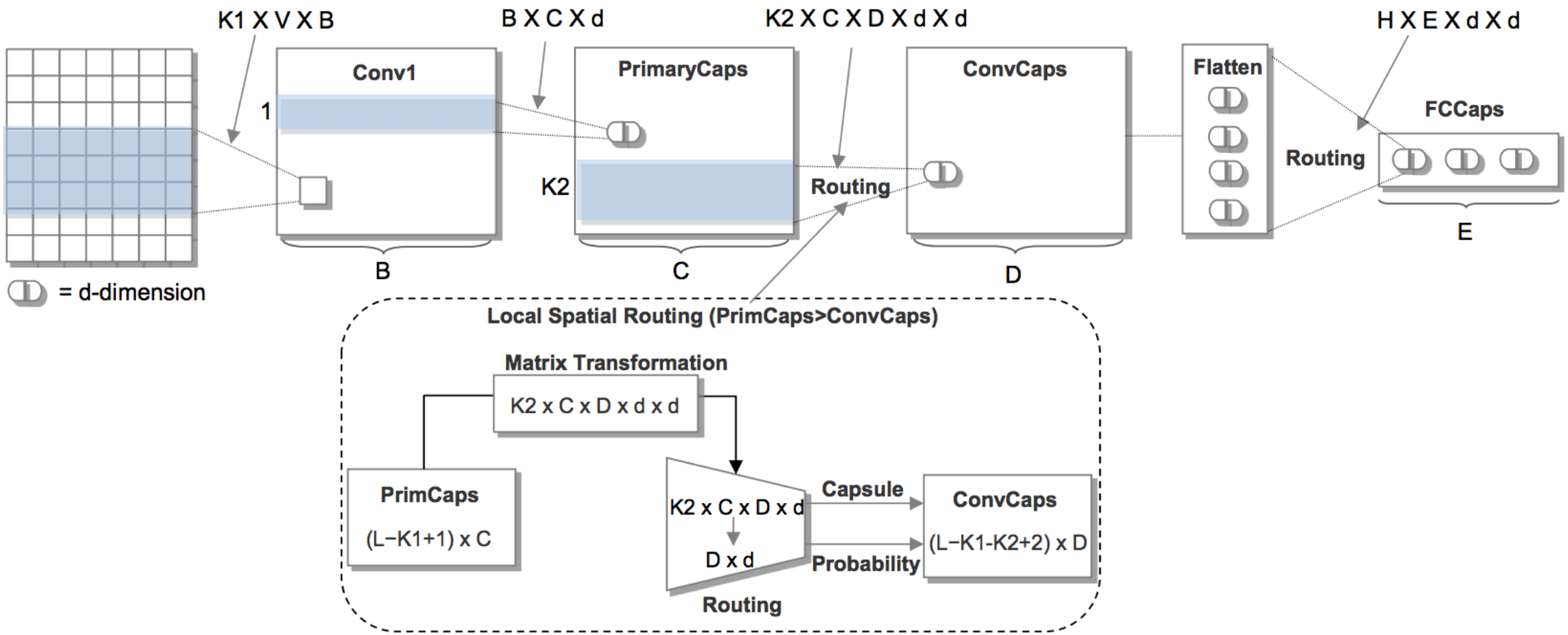
Text Classification using Capsules

Jaeyoung Kim, Sion Jang and **Sungchul Choi**
TEAMLAB, Gachon University
teamlab.gachon@gmail.com

Eunjeong Park
NAVER
lucy.park@navercorp.com

https://arxiv.org/pdf/1808.03976.pdf

Capsule Network For Text



https://arxiv.org/pdf/1804.00538.pdf

Capsule Network For Text : Dealing with Noise

Orphan Category

- Add extra class with no-category in final layer
- Background noise such as Stop Words or unimportant words redirected towards Orphan category

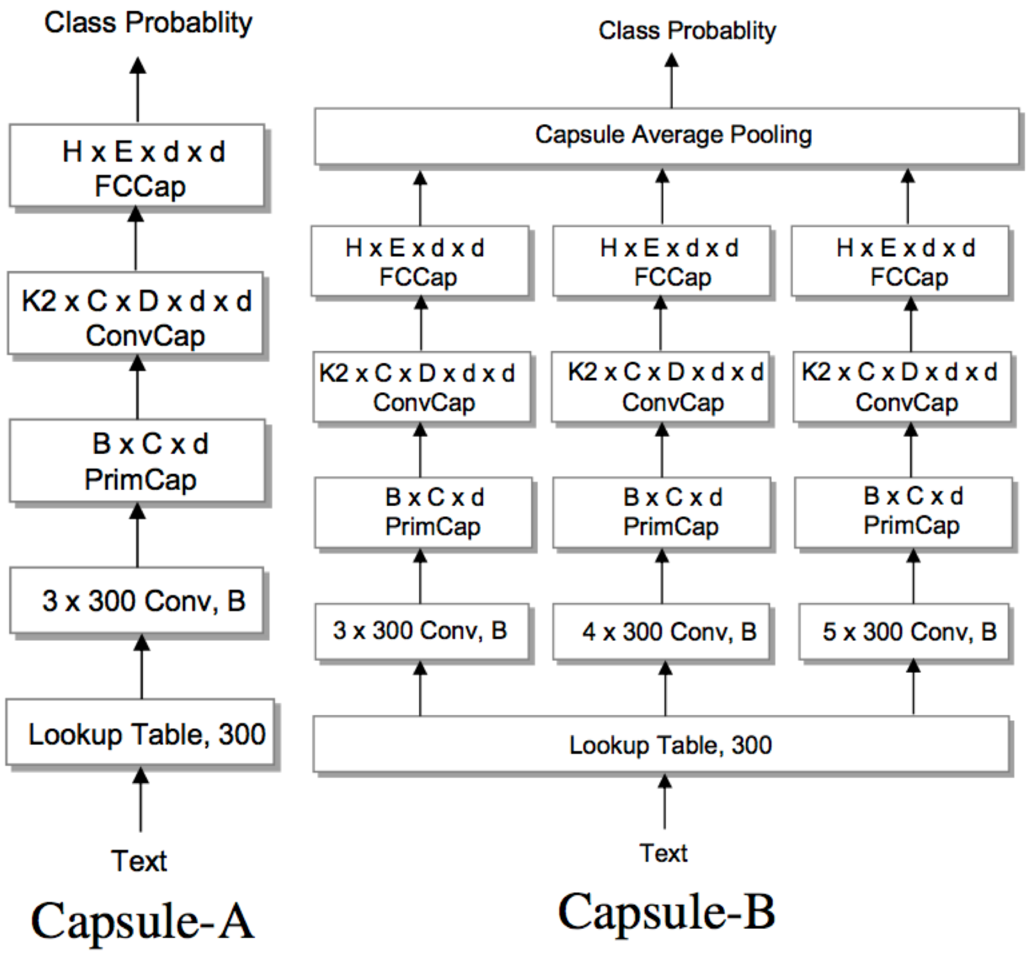
Leaky Softmax

- Leaky Softmax instead of regular Softmax
- To route the noise to orphan Category without any additional parameters and computation consuming.

https://arxiv.org/pdf/1804.00538.pdf

Capsule Network For Text

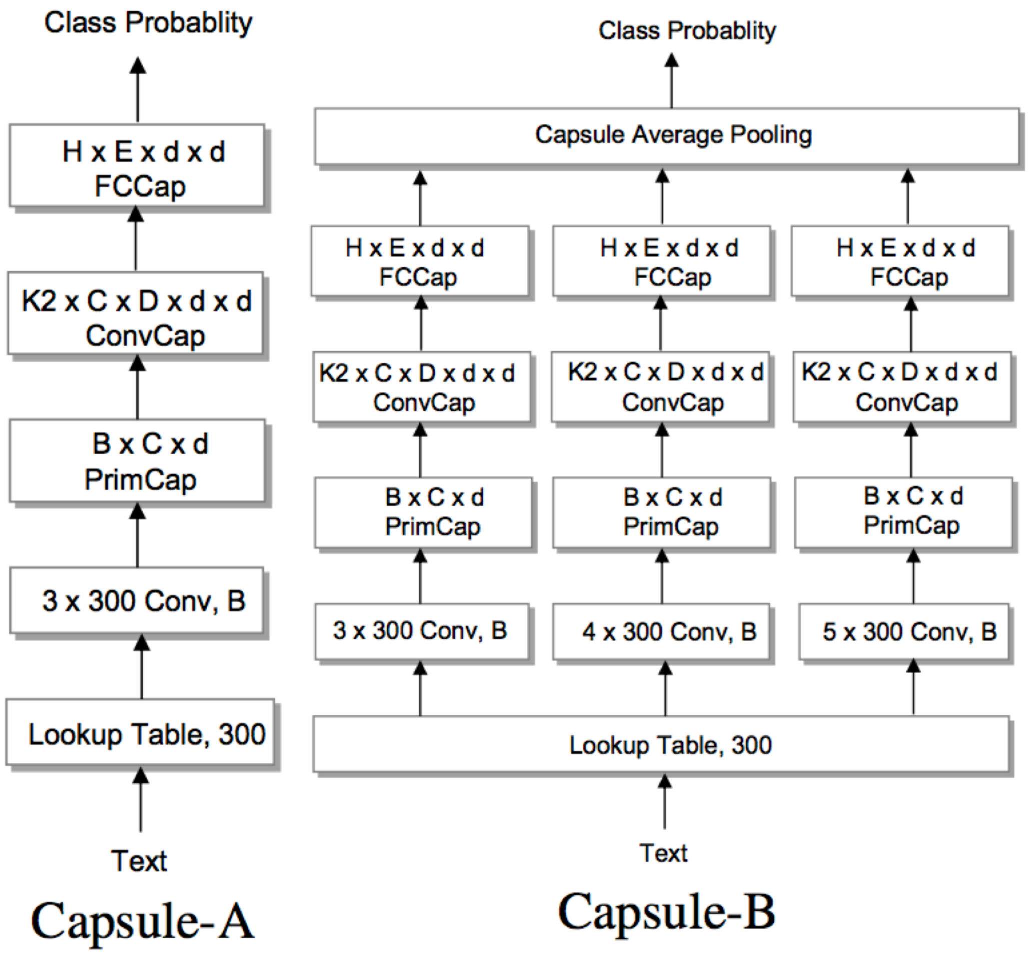
Dataset	Train	Dev	Test	Classes	Classification Task
MR	8.6k	0.9k	1.1k	2	review classification
SST-2	8.6k	0.9k	1.8k	2	sentiment analysis
Subj	8.1k	0.9k	1.0k	2	opinion classification
TREC	5.4k	0.5k	0.5k	6	question categorization
CR	3.1k	0.3k	0.4k	2	review classification
AG's news	108k	12.0k	7.6k	4	news categorization



https://arxiv.org/pdf/1804.00538.pdf

Capsule Network For Text

	MR	SST2	Subj	TREC	CR	AG's
LSTM	75.9	80.6	89.3	86.8	78.4	86.1
BiLSTM	79.3	83.2	90.5	89.6	82.1	88.2
Tree-LSTM	80.7	85.7	91.3	91.8	83.2	90.1
LR-LSTM	81.5	**87.5**	89.9	-	82.5	-
CNN-rand	76.1	82.7	89.6	91.2	79.8	92.2
CNN-static	81.0	86.8	93.0	92.8	84.7	91.4
CNN-non-static	81.5	87.2	93.4	**93.6**	84.3	92.3
CL-CNN	-	-	88.4	85.7	-	92.3
VD-CNN	-	-	88.2	85.4	-	91.3
Capsule-A	81.3	86.4	93.3	91.8	83.8	92.1
Capsule-B	**82.3**	86.8	**93.8**	92.8	**85.1**	**92.6**



https://arxiv.org/pdf/1804.00538.pdf

Capsule Network For Text : Multi-Label Classification

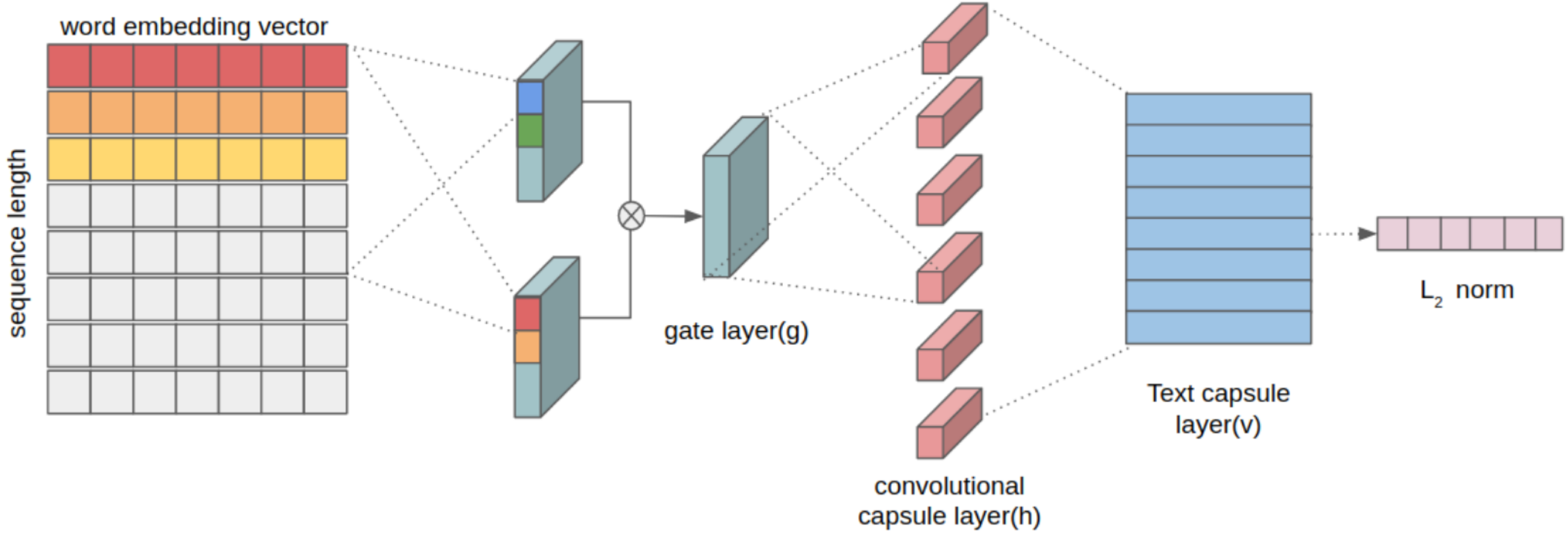
	Reuters-Multi-label			
	ER	Precision	Recall	F1
LSTM	23.3	86.7	54.7	63.5
BiLSTM	26.4	82.3	55.9	64.6
CNN-rand	22.5	88.6	56.4	67.1
CNN-static	27.1	91.1	59.1	69.7
CNN-non-static	27.4	92.0	59.7	70.4
Capsule-A	57.2	88.2	80.1	82.0
Capsule-B	**60.3**	**95.4**	**82.0**	**85.8**

Multi-Label Classification Challenges

- Label space is expanded from n to 2^n
- More labelled dataset required for CNN and LSTM to work
- Capsule performed well (better generalization by capturing patterns using capsules) without extensive labeled data

https://arxiv.org/pdf/1804.00538.pdf

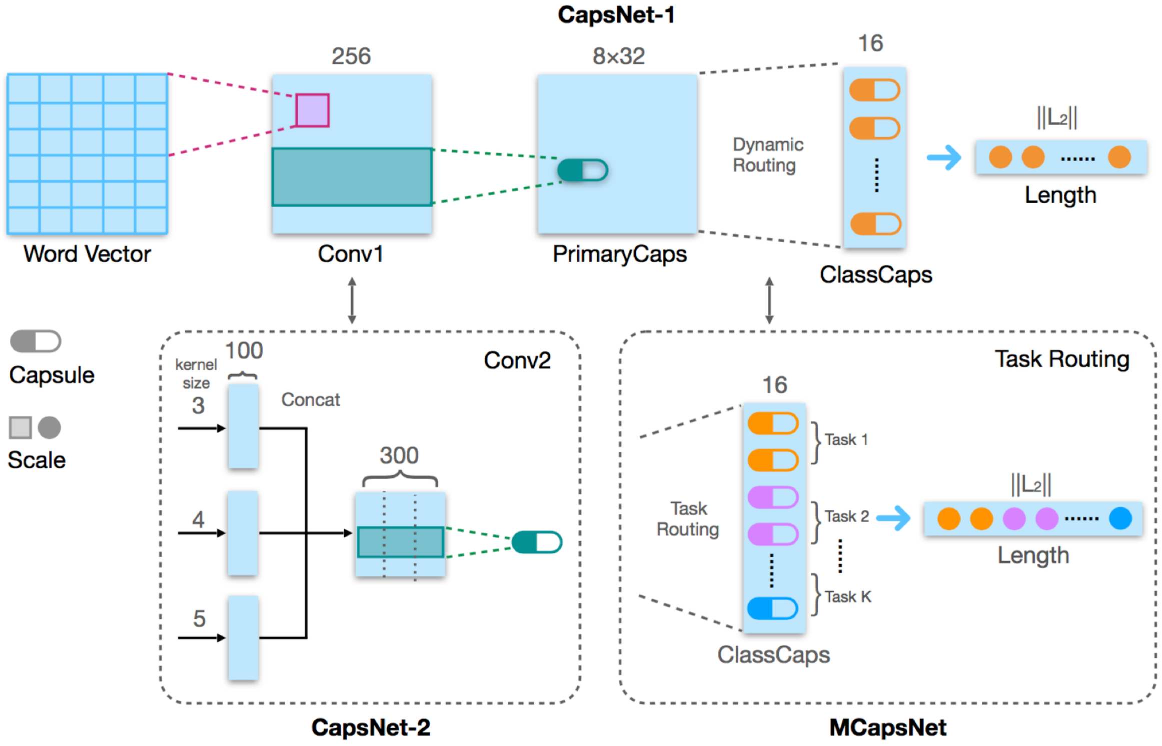
Capsule Network For Text



- Uses Gate Linear Unit (Dauphin et al., 2016) for selecting features to be activated
- Unlike Pooling , ELU gate unit doesn't lose spatial information

https://arxiv.org/pdf/1808.03976.pdf

CapsNet for Text : Multi-Task Learning



MCapsNet: Capsule Network for Text with Multi-Task Learning

Liqiang Xiao[1,2], Honglun Zhang[1,2], Wenqing Chen[1,2], Yongkun Wang[3], Yaohui Jin[1,2]
[1] State Key Lab of Advanced Optical Communication System and Network, Shanghai Jiao Tong University
[2] MoE Key Lab of Artificial Intelligence, AI Institute, Shanghai Jiao Tong University
[3] Network and Information Center, Shanghai Jiao Tong University
{jinyh}@sjtu.edu.cn

Dataset	MR	SST-1	SST-2	Subj	TREC	AG's	Avg.△
BiLSTM	79.3	46.2	83.2	90.5	89.6	88.2	+0
MT-GRNN	-	49.2	87.7	89.3	93.8	-	+2.6
MT-RNN	-	49.6	87.9	94.1	91.8	-	+3.5
MT-DNN	82.1	48.1	87.3	93.9	92.2	91.8	+2.9
MT-CNN	81.6	49.0	86.9	93.6	91.8	91.9	+3.0
CapsNet-1	81.5	48.1	86.4	93.3	91.8	91.1	+2.5
CapsNet-2	82.4	48.7	87.8	93.6	92.9	92.3	+3.3
MCapsNet	83.5	49.7	88.6	94.5	94.2	93.8	+4.6

Section 2

Industrialization of Capsule Networks

Platform

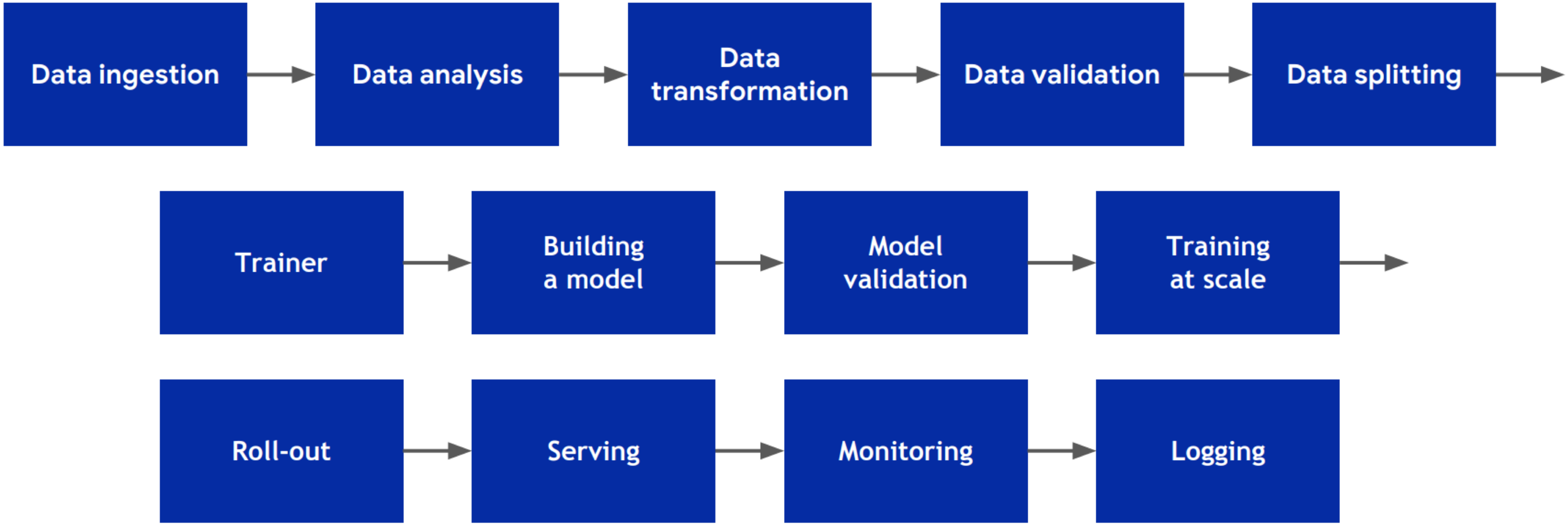
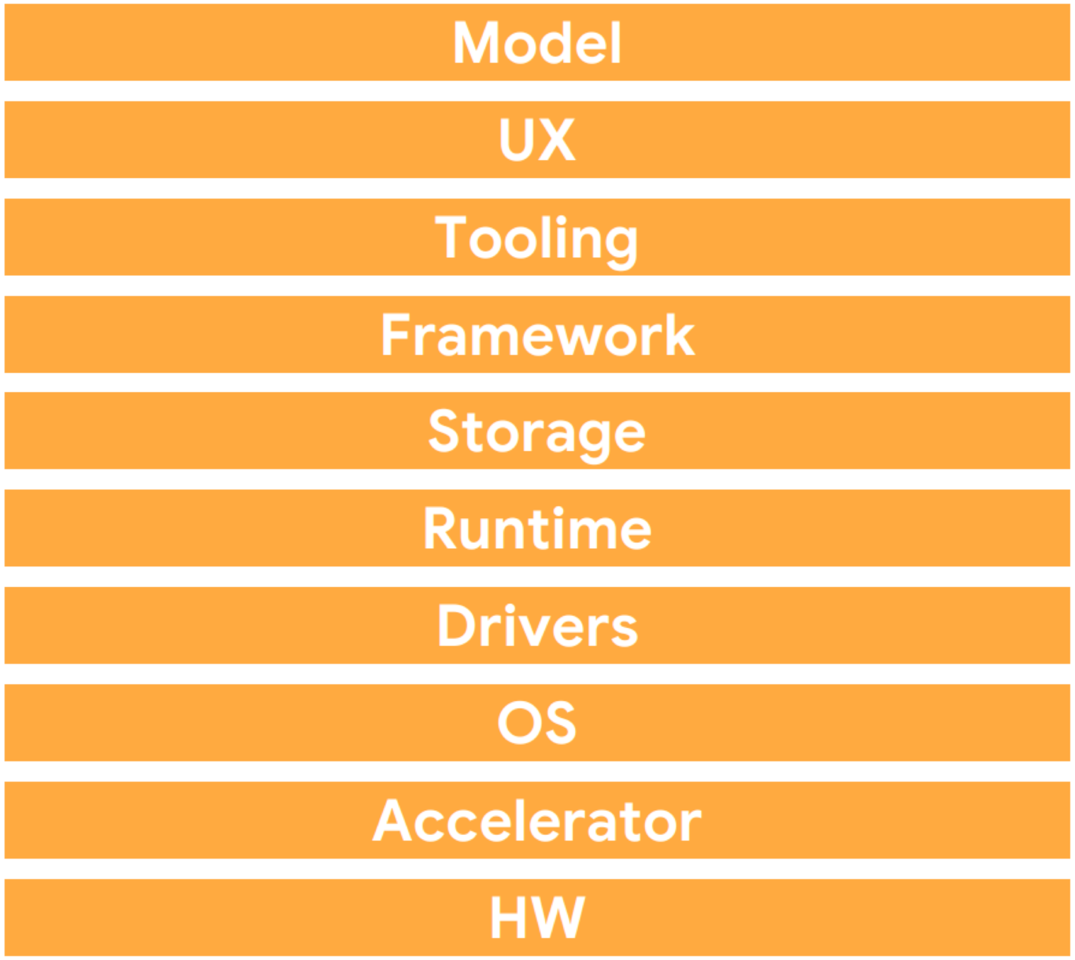


*Image Credits : “Machine Learning as code” at Kubecon 2018 by David Aronchick and Jason Smith

Experimentation



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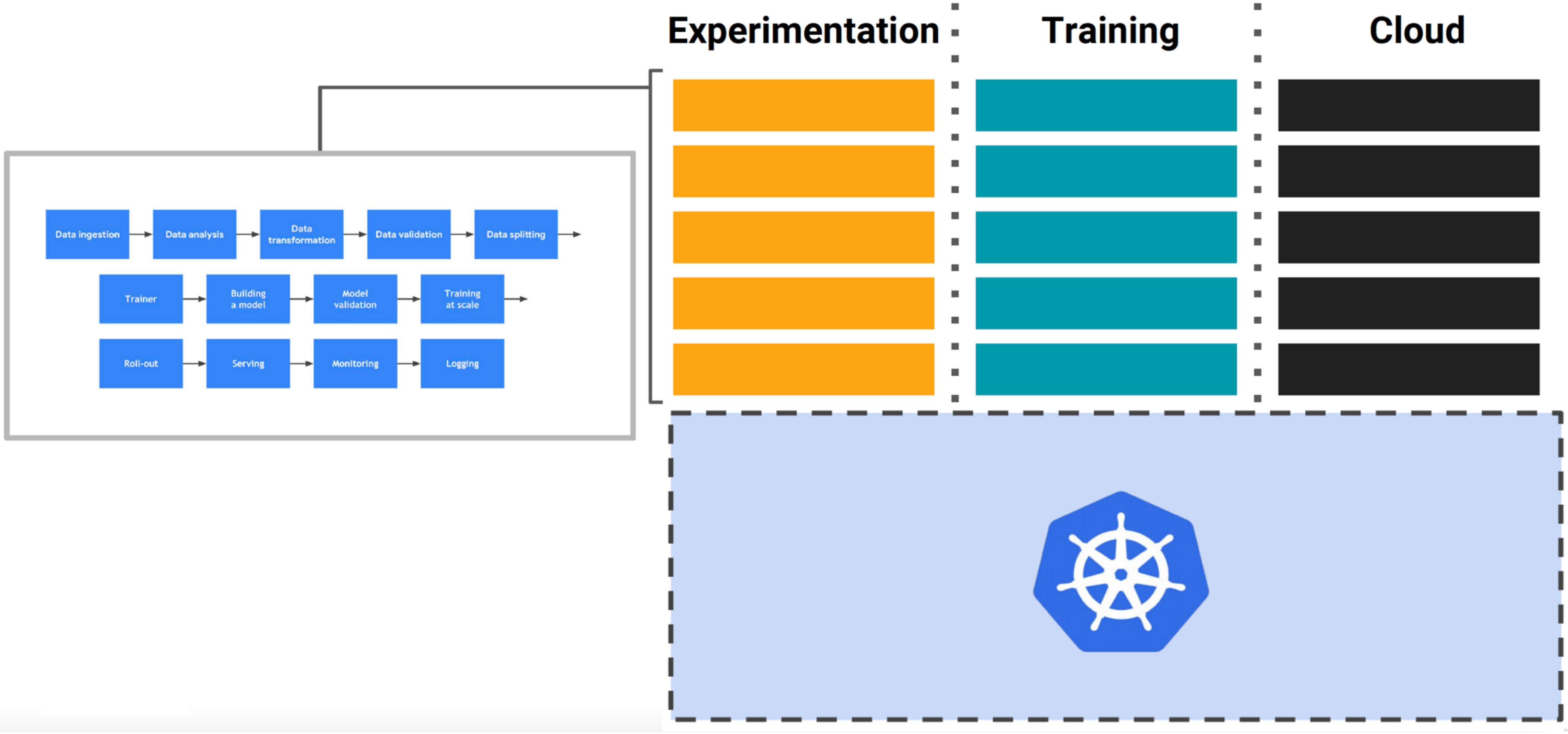
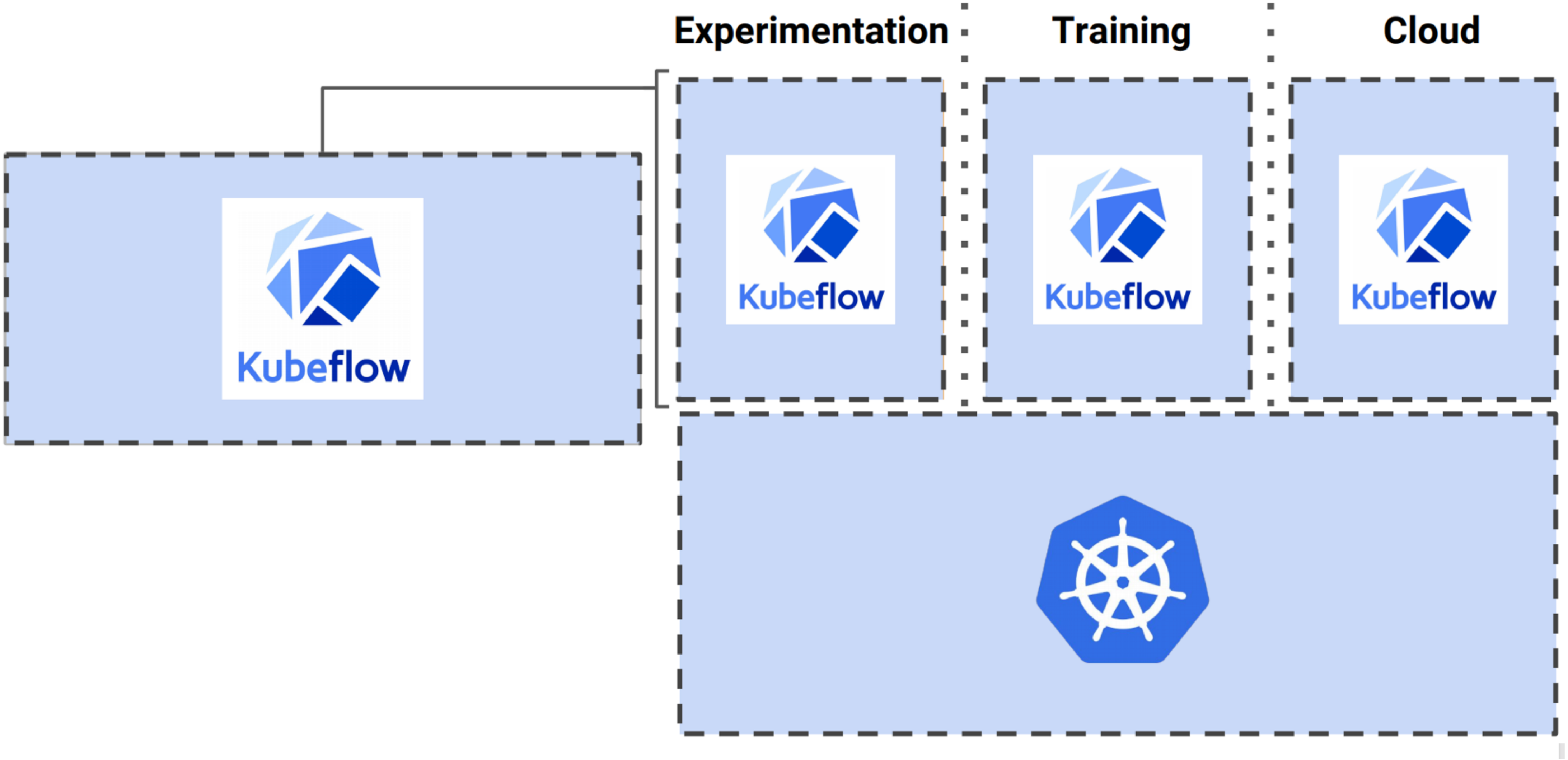


*Image Credits : “Machine Learning as code” at Kubecon 2018 by David Aronchick and Jason Smith

You want to run ML on K8S?

First, can you become an expert in

- Containers
- Packaging
- Kubernetes service endpoints
- Persistent Volumes
- Scaling
- Immutable deployments
- GPUs, Drivers & GPL
- Cloud APIs
- DevOps
- ...



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What is Kubeflow ?

"The Machine Learning Toolkit for Kubernetes"

A curated set of compatible tools and artifacts that lays a foundation for running production ML apps

Notebook

TF Model Training

TF serving
Seldon,
TensorRT

Pipelines

Multi-framework
Integration

Components List

Training

- Tensorflow Training
- Pytorch Training
- Chainer Trainiing
- MPI Training
- MXNet Training

Serving

- Tensorflow Serving
- Pytorch Serving
- Seldon Serving

Prediction

- Tensorflow Batch Prediction
- NVIDIA TensorRT Inference

Model Development

- Jupyter Notbeook
- Hyper-parameter Tuning (Katib)

Orchestration

- Pipelines

Training & Development Library

- Fairing

Tooling

- Ksonnet

Metadata Management

- ModelDB

Service Mesh

- Instio Integration

Tenets

Composable

Use the libraries / frameworks of your choice

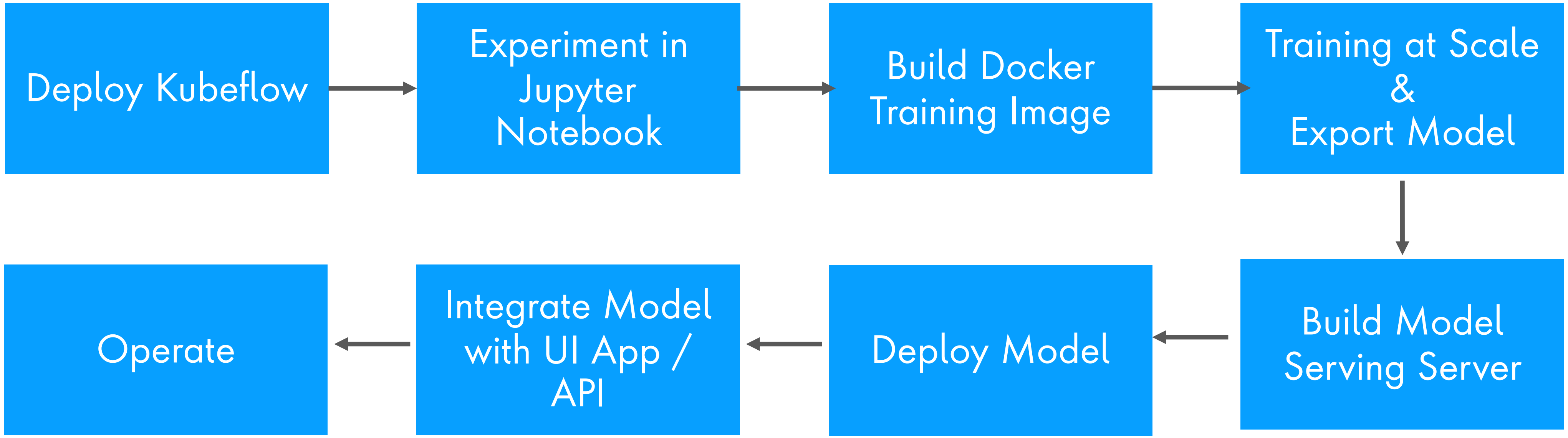
Scalable

number of users & workload size

Portable

on prem, public cloud, local

Typical Workflow



Key Summary and Demo

- Kubeflow : running capsnet on Kubeflow
- Notebooks with GPU configuration (Multi-GPU training Strategy)
- TF Job : Distributed jobs
- Katib for Hyper-Parameter Tuning

Basic Implementation using Tensorflow

```python
def squash(x, axis=-1):
    s_squared_norm = K.sum(K.square(x), axis, keepdims=True) + K.epsilon()
    scale = K.sqrt(s_squared_norm)/ (0.5 + s_squared_norm)
    return scale * x


#define our own softmax function instead of K.softmax
def softmax(x, axis=-1):
    ex = K.exp(x - K.max(x, axis=axis, keepdims=True))
    return ex/K.sum(ex, axis=axis, keepdims=True)
```

```python
def call(self, u_vecs):
    if self.share_weights:
        u_hat_vecs = K.conv1d(u_vecs, self.W)
    else:
        u_hat_vecs = K.local_conv1d(u_vecs, self.W, [1], [1])

    batch_size = K.shape(u_vecs)[0]
    input_num_capsule = K.shape(u_vecs)[1]
    u_hat_vecs = K.reshape(u_hat_vecs, (batch_size, input_num_capsule,
                                        self.num_capsule, self.dim_capsule))
    u_hat_vecs = K.permute_dimensions(u_hat_vecs, (0, 2, 1, 3))
    #final u_hat_vecs.shape = [None, num_capsule, input_num_capsule, dim_capsule]

    b = K.zeros_like(u_hat_vecs[:,:,:,0]) #shape = [None, num_capsule, input_num_capsule]
    for i in range(self.routings):
        c = softmax(b, 1)
        o = K.batch_dot(c, u_hat_vecs, [2, 2])
        if i < self.routings - 1:
            o = K.l2_normalize(o, -1)
            b = K.batch_dot(o, u_hat_vecs, [2, 3])
    return self.activation(o)

def compute_output_shape(self, input_shape):
    return (None, self.num_capsule, self.dim_capsule)
```

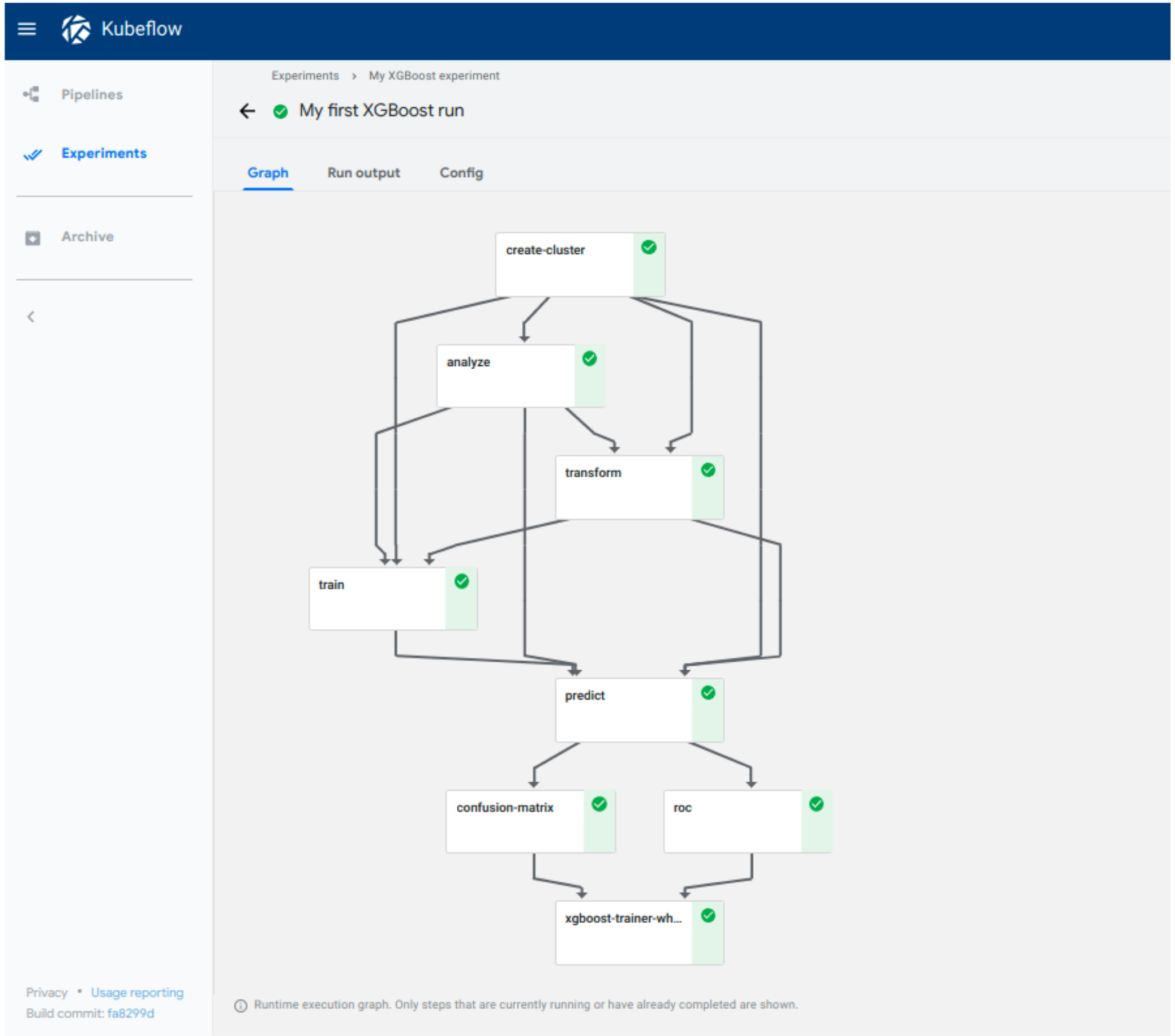
Distribution Strategy

- Converting Keras Model to Estimator
- Use Mirrored Strategy

```
config = tf.estimator.RunConfig(
    experimental_distribute=tf.contrib.distribute.DistributeConfig(
        train_distribute=tf.contrib.distribute.CollectiveAllReduceStrategy(
            num_gpus_per_worker=0),
        eval_distribute=tf.contrib.distribute.MirroredStrategy(
            num_gpus_per_worker=0)))
```

Pipelines

- End-to-end ML Workflows in CI/CD
- Orchestration
- Service Integration
- Components & Sharing
- Job Tracking , experimentation
- Notebook Integration



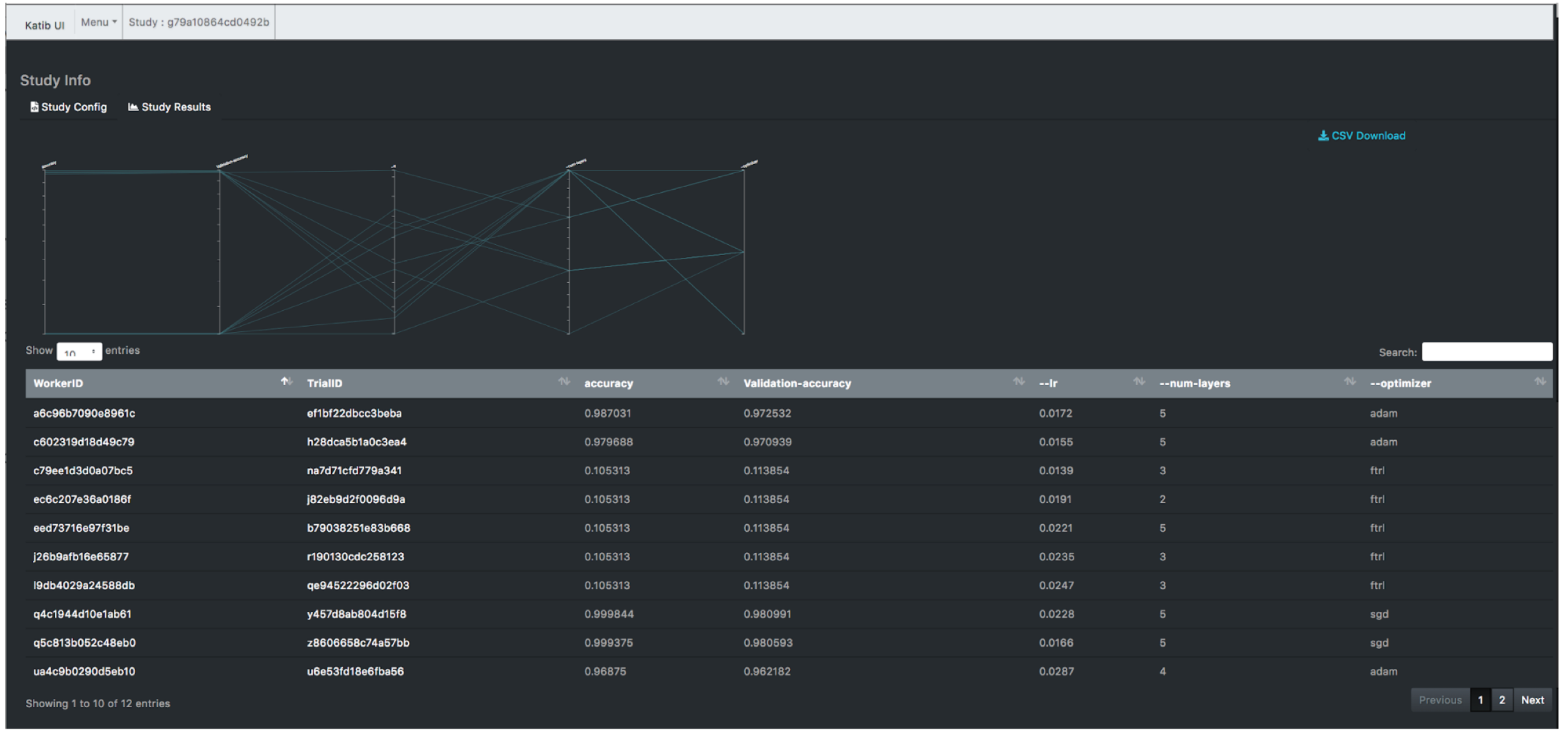
Hyper-Parameter Tuning

Katib (by NTT)

- Pluggable micro-service
- Multiple architecture for Hyper-Parameter tuning (Grid, Random, Bayesian, Hyperband)
- Different optimization algorithms
  Different frameworks

StudyJob (K8s CRD)

- Hides complexity from user
- No code needed to do hyper-parameter tuning



Further Exploration (Efficiency Side)

- Trying Efficient Routing Algorithm
- Use Matrix Capsules instead of Vector Capsules
- Tensorflow Code Optimization

Fast Dynamic Routing Based on Weighted Kernel Density Estimation

Suofei Zhang[1], Wei Zhao[2], Xiaofu Wu[1], Quan Zhou[1]

[1]Nanjing University of Post and Telecommunication
[2]SIAT, Chinese Academy of Sciences

https://arxiv.org/pdf/1805.10807.pdf

MATRIX CAPSULES WITH EM ROUTING

Geoffrey Hinton, Sara Sabour, Nicholas Frosst
Google Brain
Toronto, Canada
{geoffhinton, sasabour, frosst}@google.com

https://openreview.net/pdf?id=HJWLfGWRb

Next Steps

- Provide feedback on the tutorial
- Session Content
  - http://bit.ly/aiconf2019
  - Know more on Kubeflow (Strata SFO, 2019)
    - http://bit.ly/deep-recsys
- Share
  - Progress, Issues, Use-cases
  - Connect on LinkedIn
  - Twitter
    - @a_vijaysrinivas
    - @meabhishekkumar

thank you

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