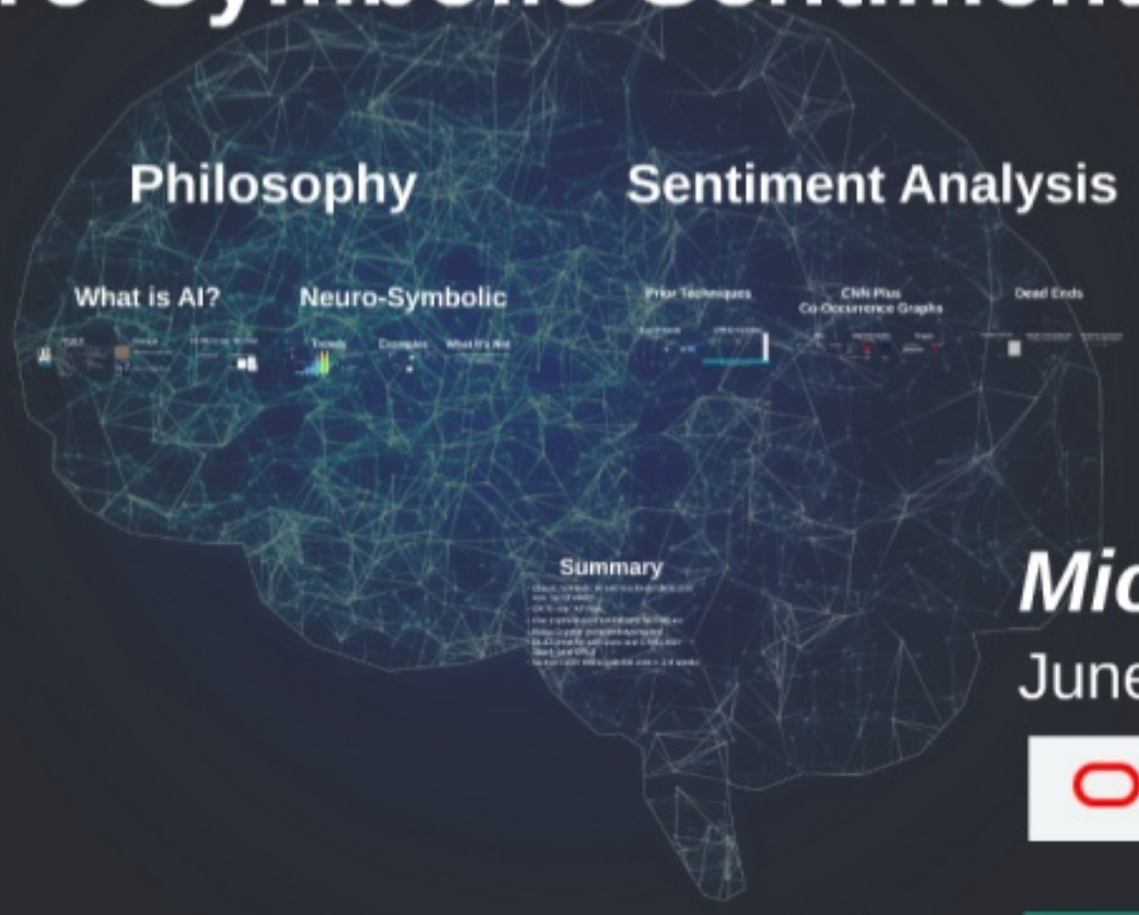
Neuro-Symbolic Sentiment Analysis



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Neuro-Symbolic Sentiment Analysis

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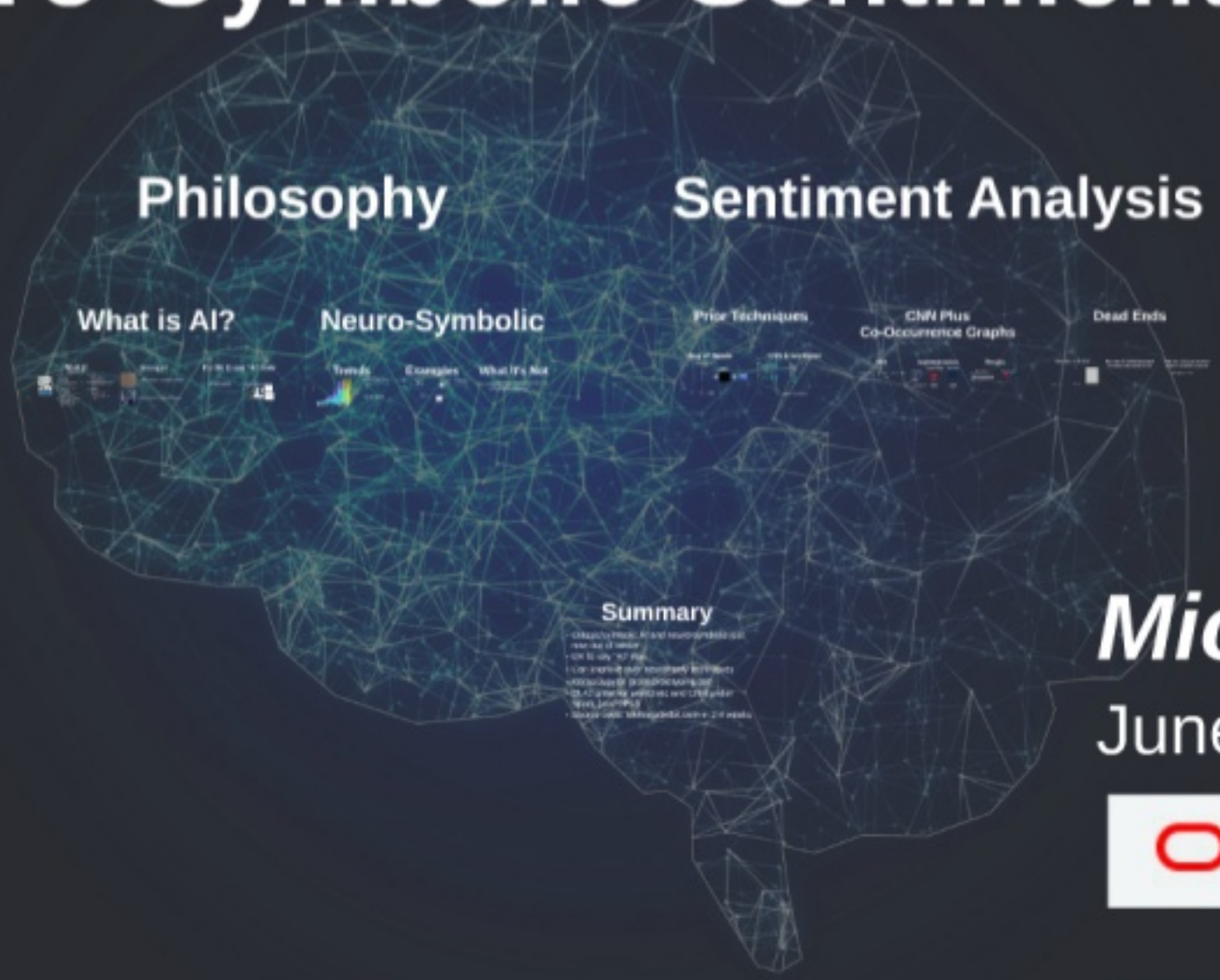
Neuro-Symbolic Sentiment Analysis



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Philosophy

What is AI?

Weak AI

Classic AI

Strong AI

Artificial General Intelligence (AGI)

Artificial Super Intelligence (ASI)

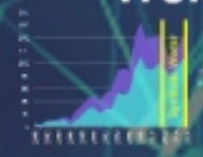
It's OK to say "AI" now

AI Permadrost

Silicon Valley AI Depts

Neuro-Symbolic

Trends



Examples

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- NTM (Neural Turing Machines)

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- 1 Introduction
- 2 Intelligent Agents

Part II Problem Solving
- 3 Solving Problems by Searching
- 4 Beyond Classical Search
- 5 Adversarial Search
- 6 Constraint Satisfaction Problems

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- 8 First-Order Logic
- 9 Inference in First-Order Logic
- 10 Classical Planning
- 11 Planning and Acting in the Real World
- 12 Knowledge Representation

Part IV Uncertain Knowledge and Reasoning
- 13 Quantifying Uncertainty
- 14 Probabilistic Reasoning
- 15 Probabilistic Reasoning over Time
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- 17 Making Complex Decisions

Part V Learning
- 18 Learning from Examples
- 19 Knowledge in Learning
- 20 Learning Probabilistic Models
- 21 Reinforcement Learning

Part VI Communicating, Perceiving, and Acting
- 22 Natural Language Processing
- 23 Natural Language for Communication
- 24 Perception
- 25 Robotics

Part VII Conclusions
- 26 Philosophical Foundations
- 27 AI: The Present and Future

A Mathematical Background

B Notes on Languages and Algorithms

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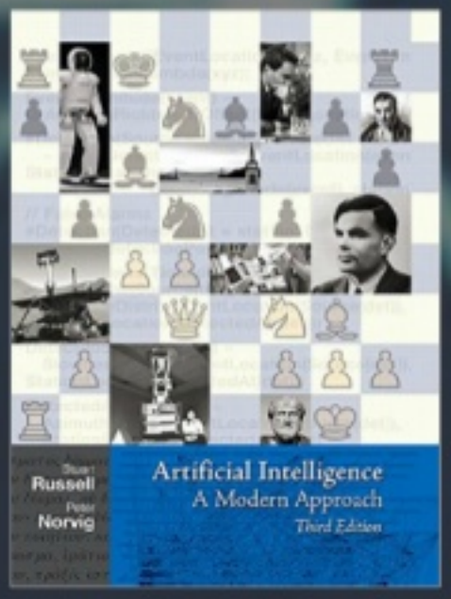

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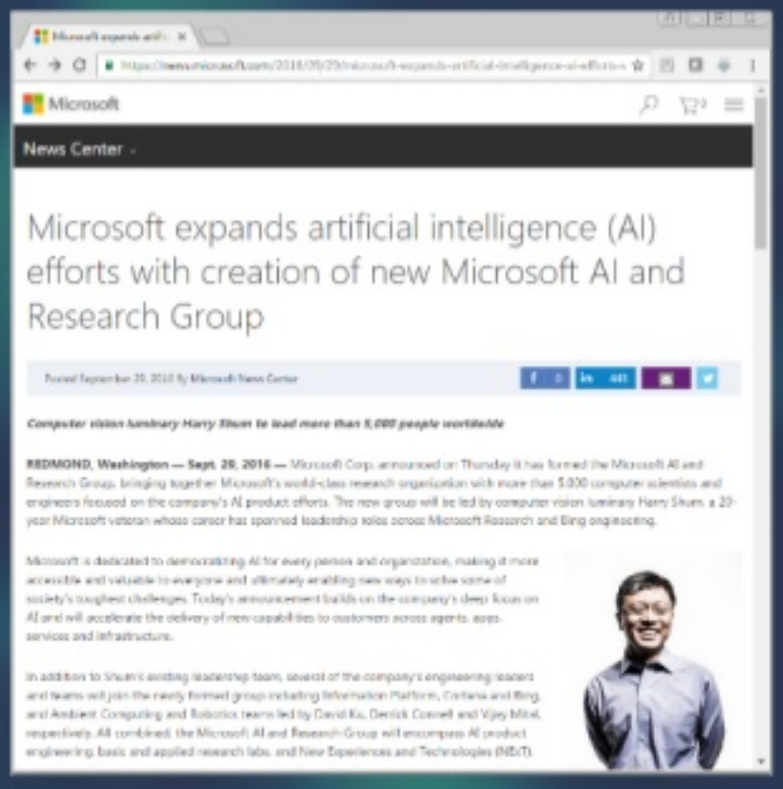

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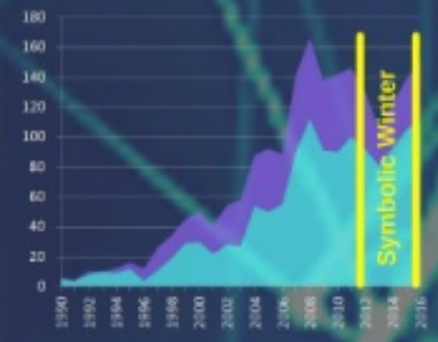

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- Some papers contain both terms
- Some contain term only in references
- Some papers are on cognitive psychology

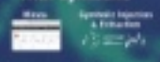
- Infrequently used term NSI: Neural Symbolic Integration

Examples

word2vec

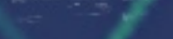
Towards AGI

Enhance neural with symbolic



Enhance symbolic with neural

Pipelines



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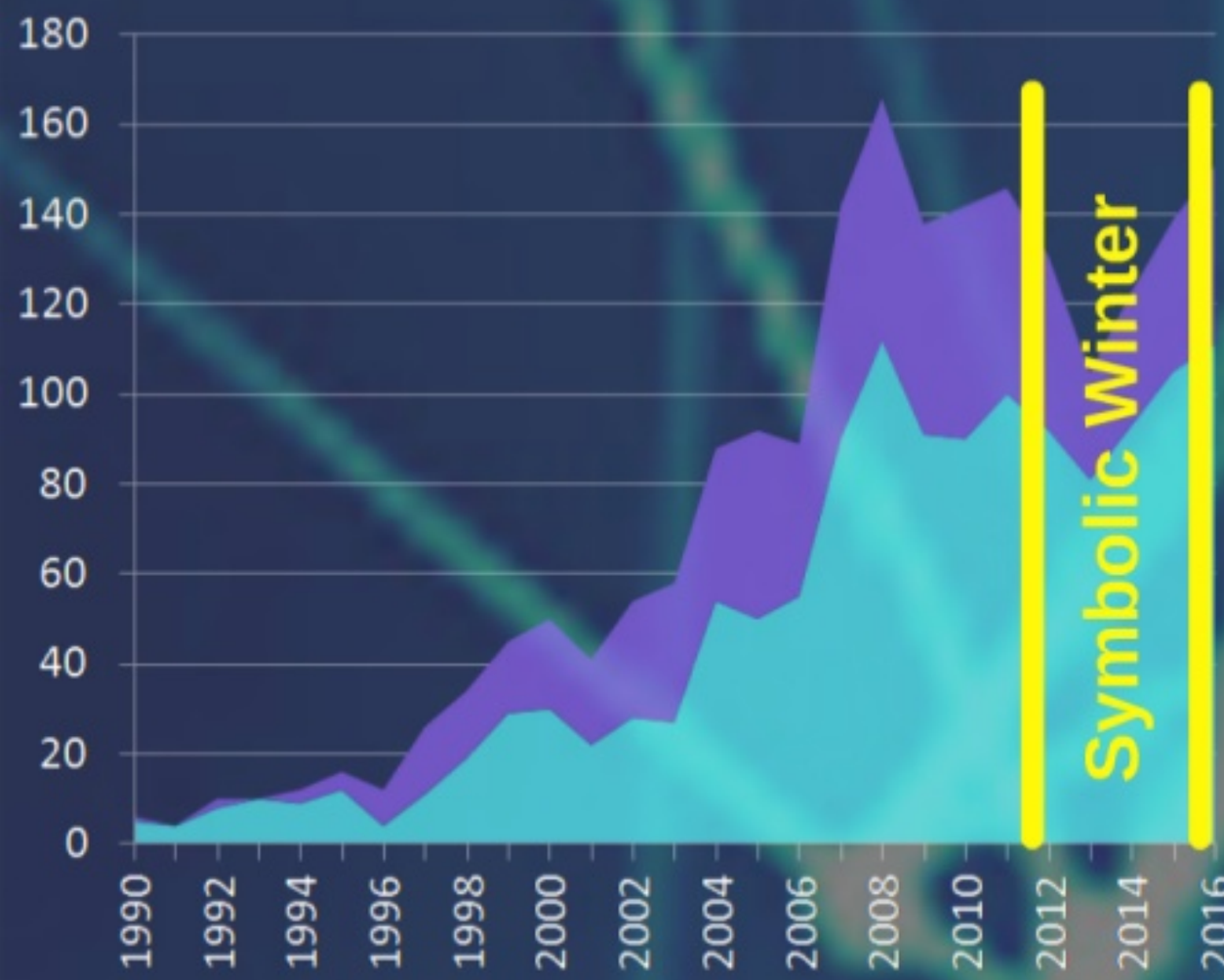

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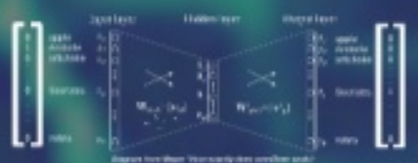

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Towards AGI

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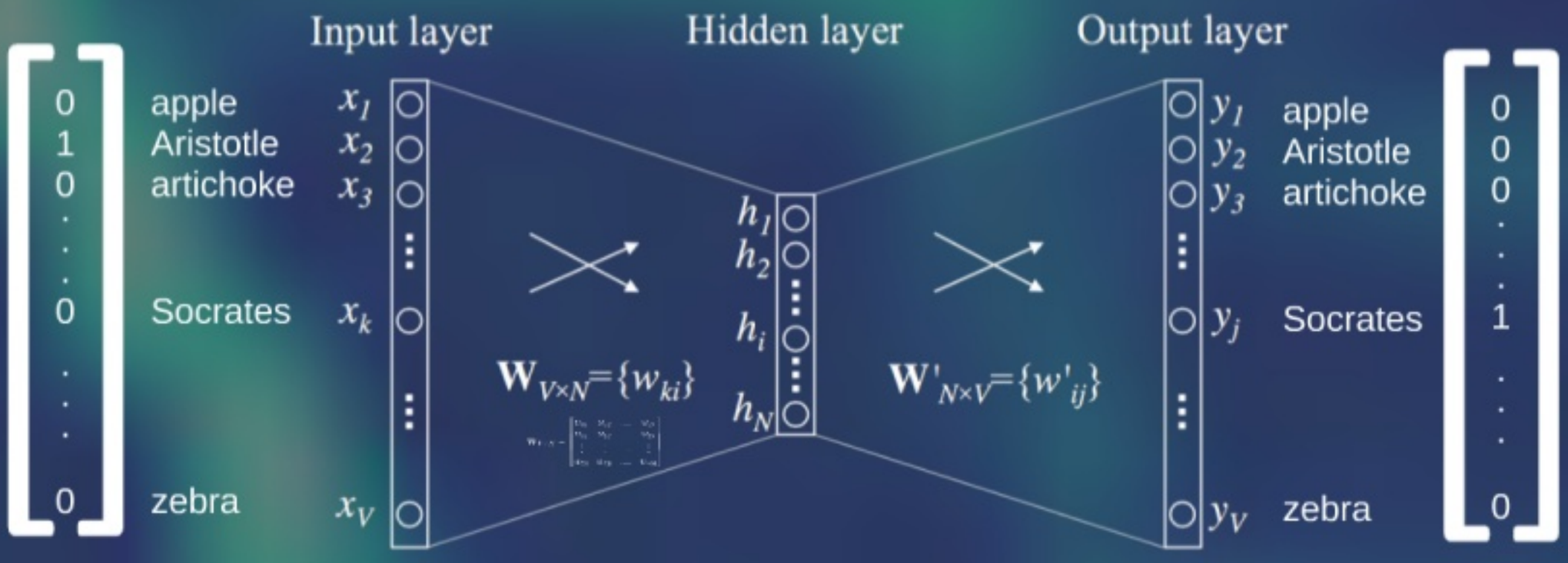

Diagram from Meyer "How exactly does word2vec work?

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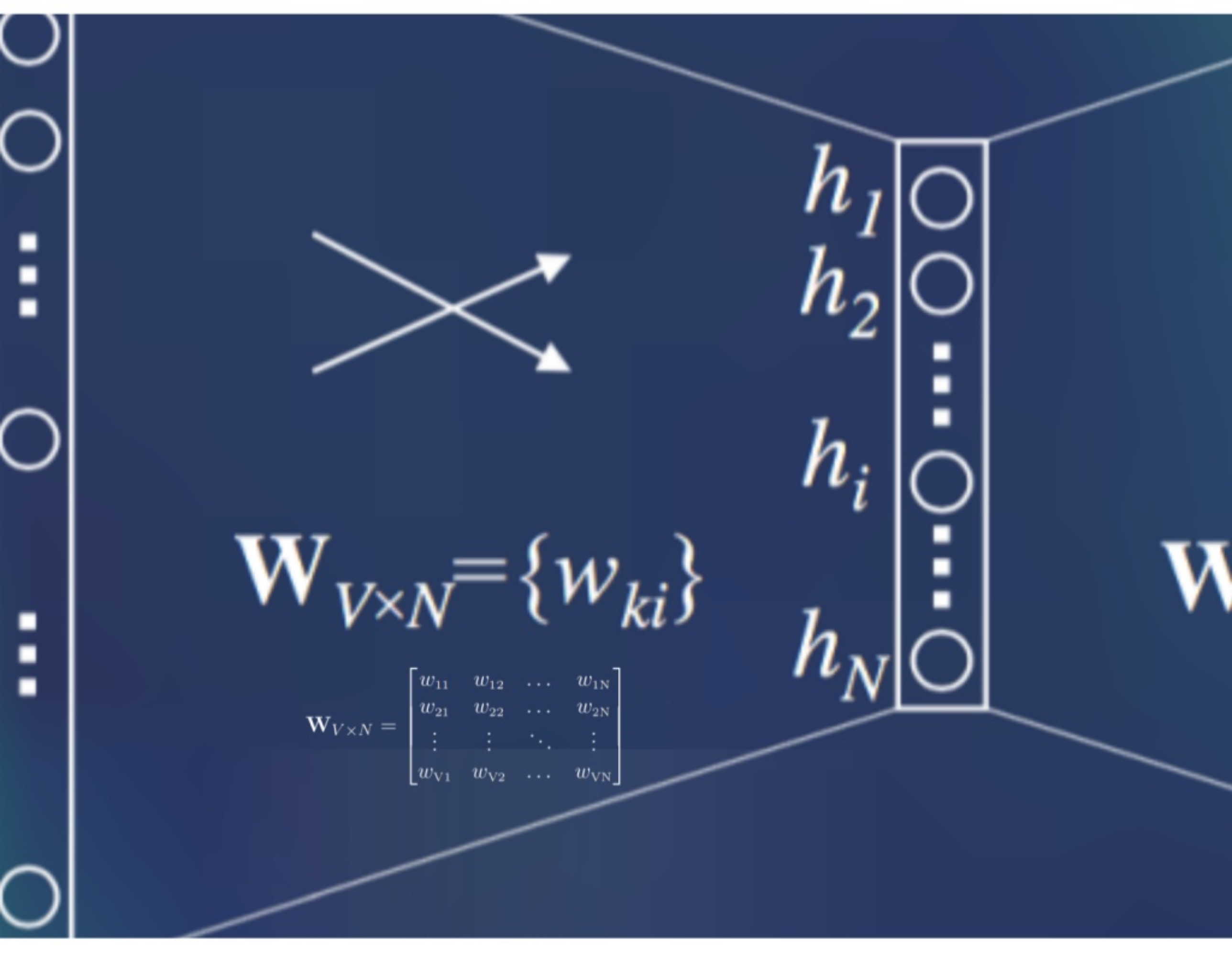
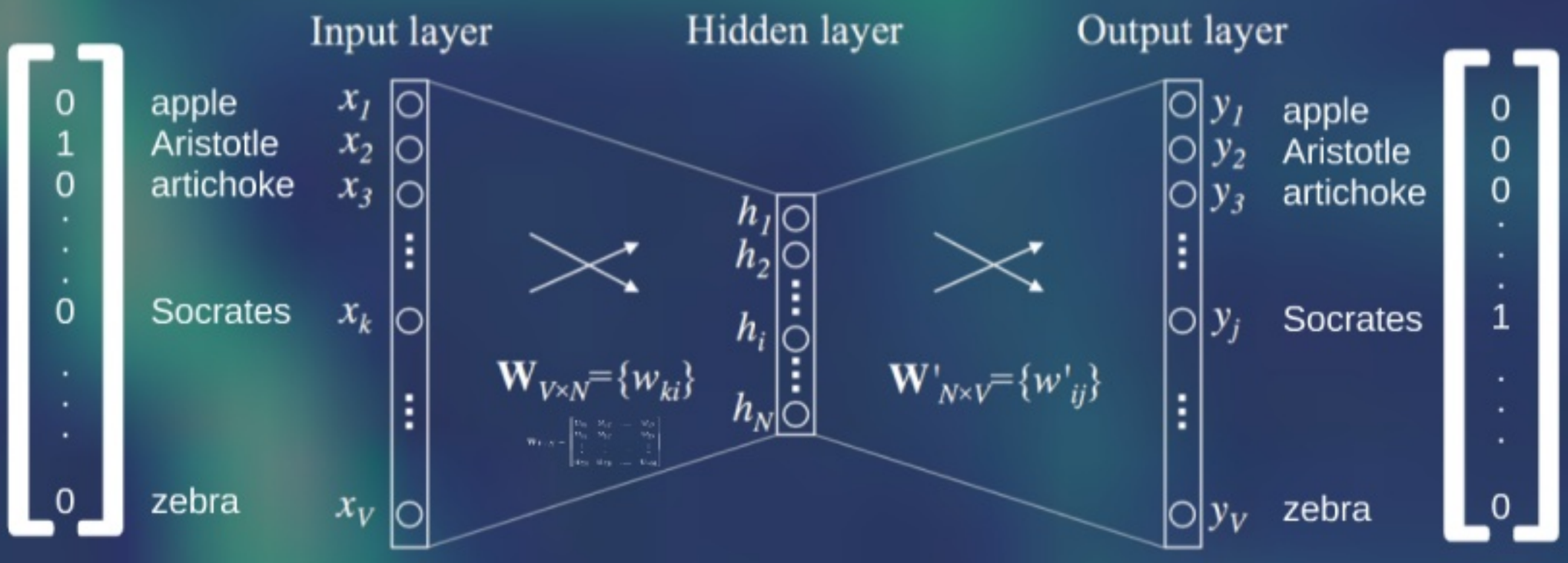

h_1
h_2
h_i
h_N
$\mathbf{W}_{V\times N}=\{w_{ki}\}$
$\mathbf{W}_{V\times N}=\begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1N} \\ w_{21} & w_{22} & \cdots & w_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ w_{V1} & w_{V2} & \cdots & w_{VN} \end{bmatrix}$
W

word2vec



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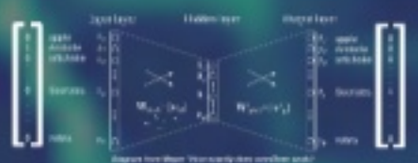

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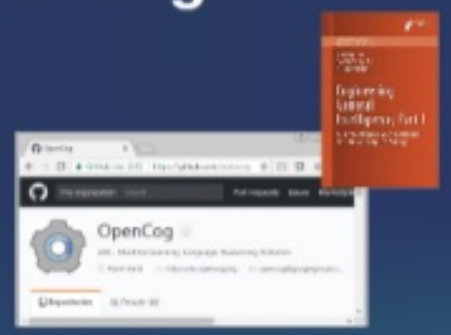
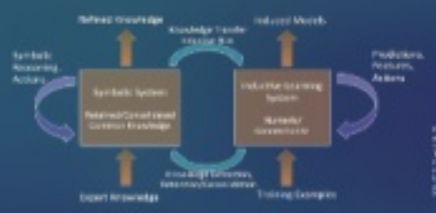
OpenCog

Diagram from goertzel.org

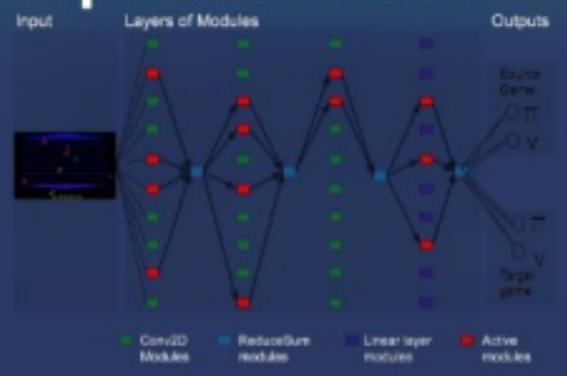


Deep Symbolic Reinforcement Learning

LML: Lifelong Machine Learning



DeepMind's PathNet



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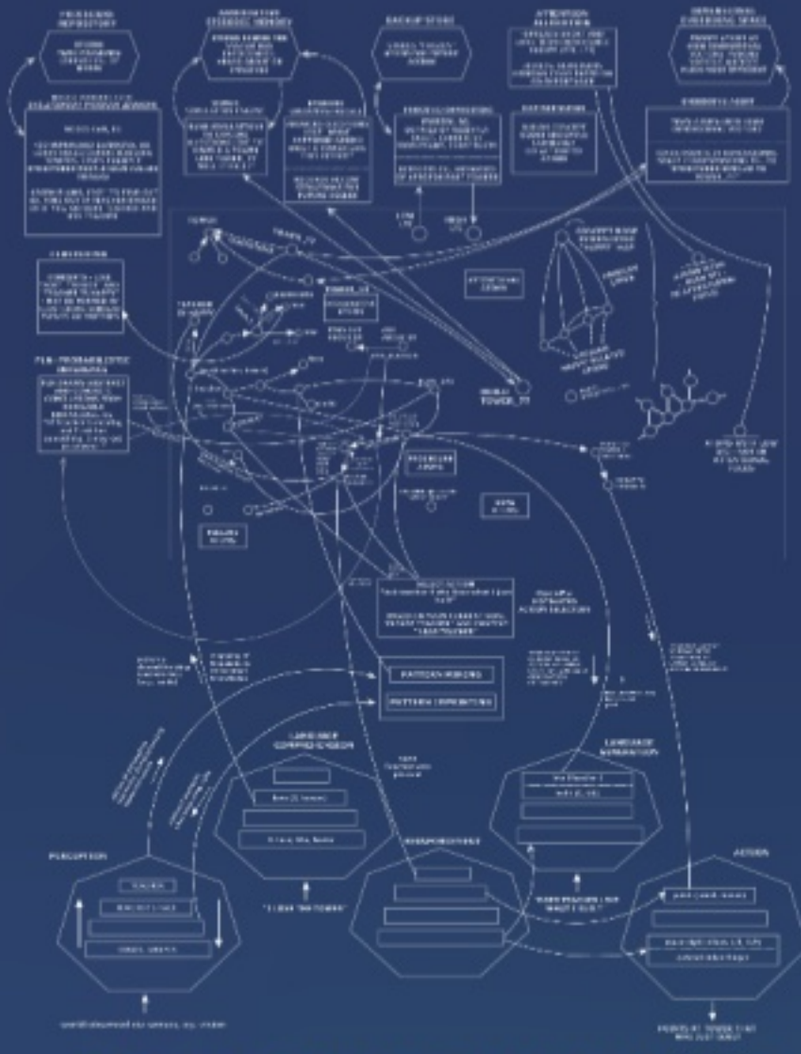

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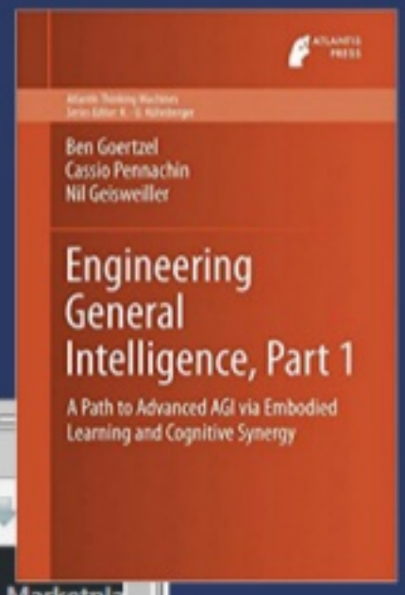

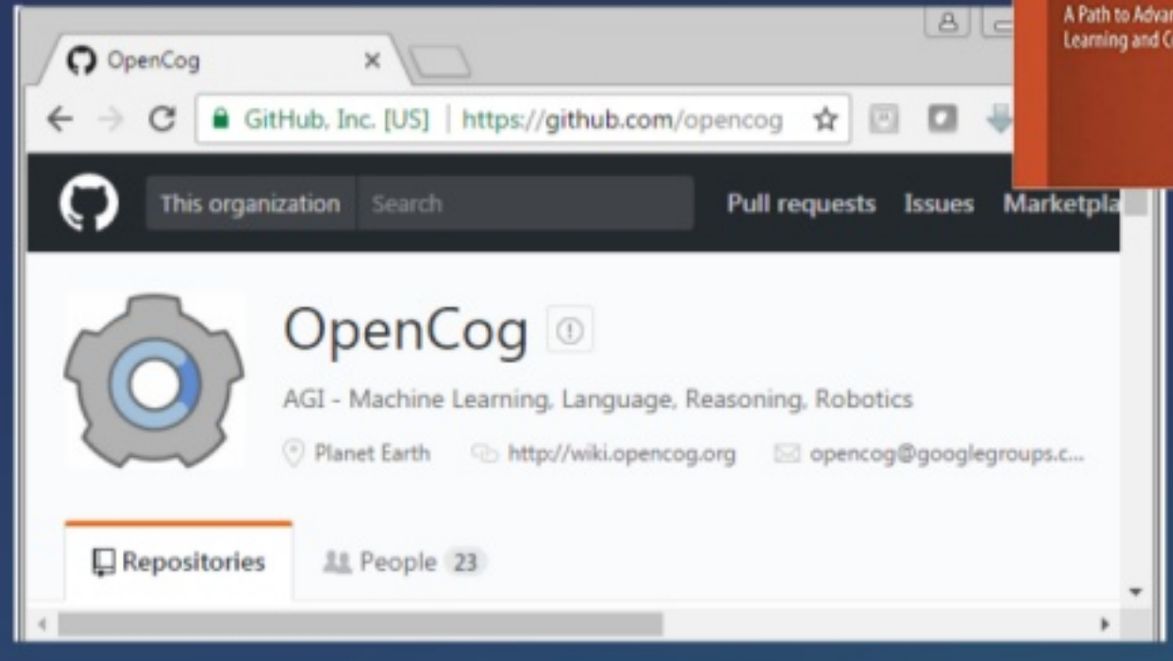

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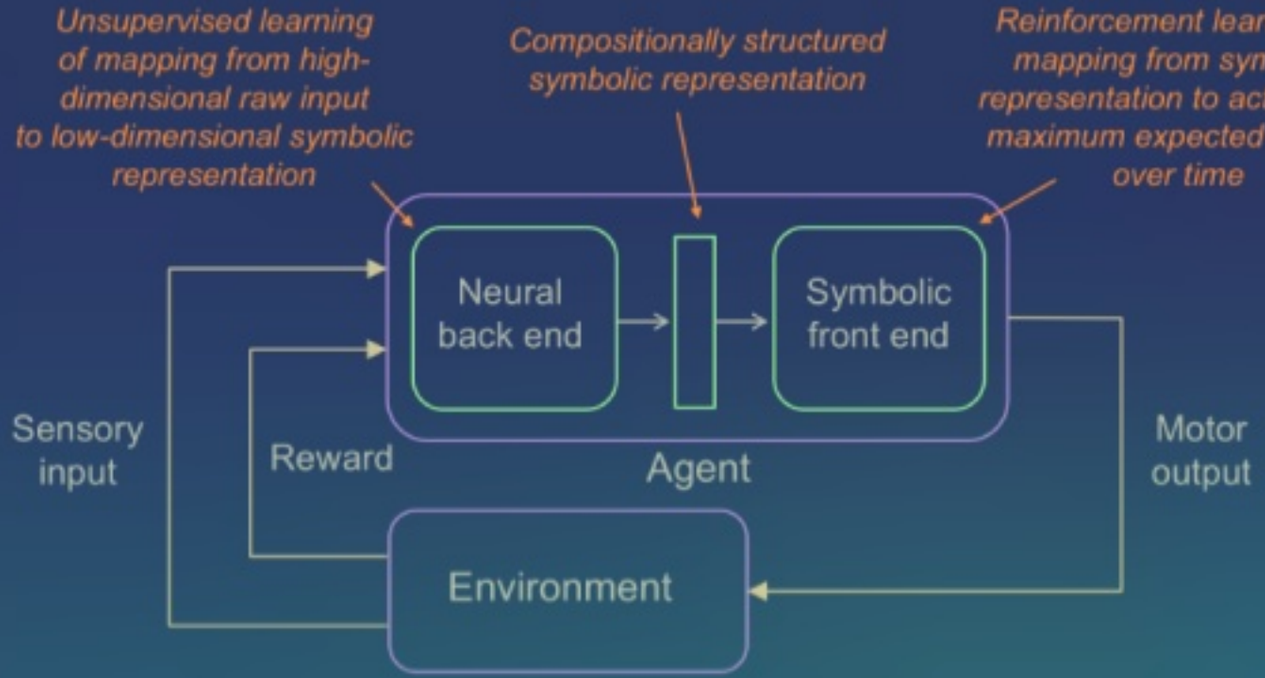

Towards Deep Symbolic Reinforcement Learning

Marta Garnelo
Department of Computing
Imperial College London
London, SW7 2AZ
garnelo@ic.ac.uk

Kai Arulkumaran
Department of Bioengineering
Imperial College London
London, SW7 2AZ
kailash.arulkumaran13@ic.ac.uk

Murray Shanahan
Department of Computing
Imperial College London
London, SW7 2AZ
m.shanahan@ic.ac.uk

Abstract

Deep reinforcement learning (DRL) brings the power of deep neural networks to bear on the generic task of trial-and-error learning, and its effectiveness has been convincingly demonstrated on tasks such as Atari video games and the game of

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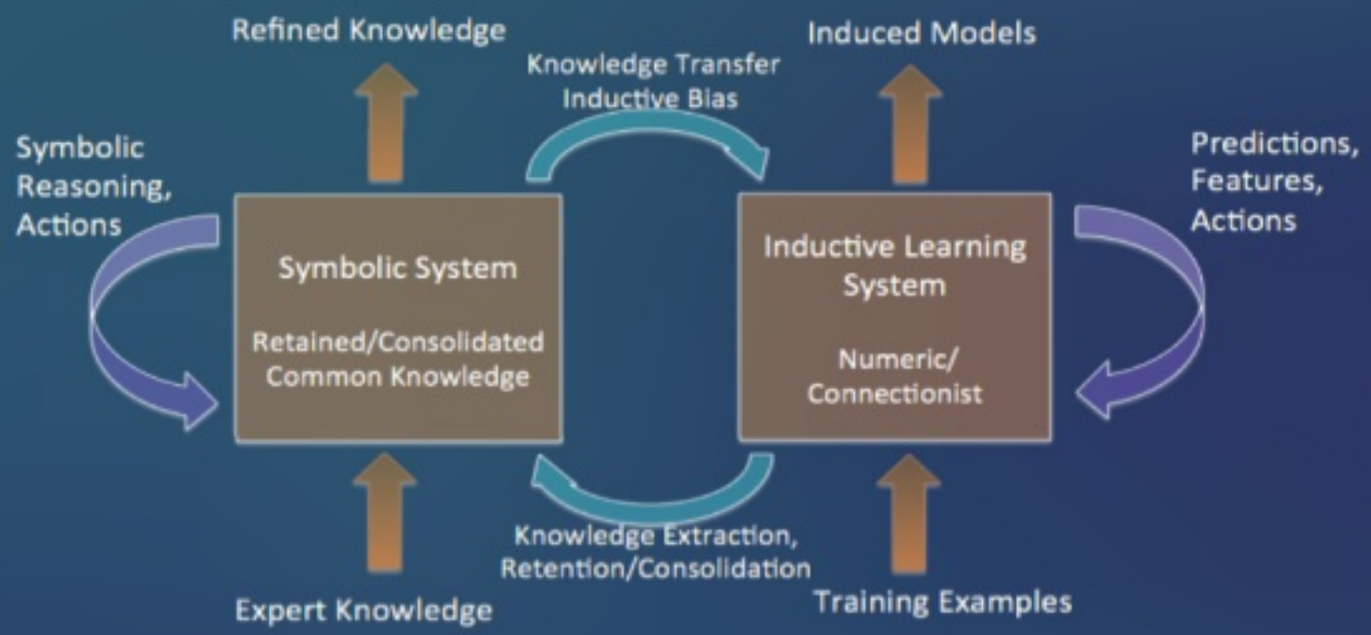

On Common Ground: Neural-Symbolic Integration and Lifelong Machine Learning

Daniel L. Silver
Acadia University
Nova Scotia, Canada
danny.silver@acadiau.ca

Abstract

Research efforts in Neural-Symbolic Integration and Lifelong Machine Learning have taken place with limited interactions over the last 20 years. These two areas of artificial intelligence share common ground and yet have much to learn from each other. This paper provides background, particularly on Lifelong Machine Learning, and presents a number of common areas of investigation with Neural-Symbolic Integration. It then invites re-

and connectionist paradigms of artificial intelligence for both learning and reasoning [Garcez *et al.*, 2002; Garcez and Gabbay, 2004].

NSI seeks to make use of the learning capacities of neural network models and the reasoning capacities of logic [Garcez *et al.*, 2014]. In a NSI system, neural networks provide the machinery for parallel computation and robust learning, while symbolic logic provides knowledge representation and reasoning. The retention of symbolic knowledge of learned models can be used for transfer learning, explanation of the

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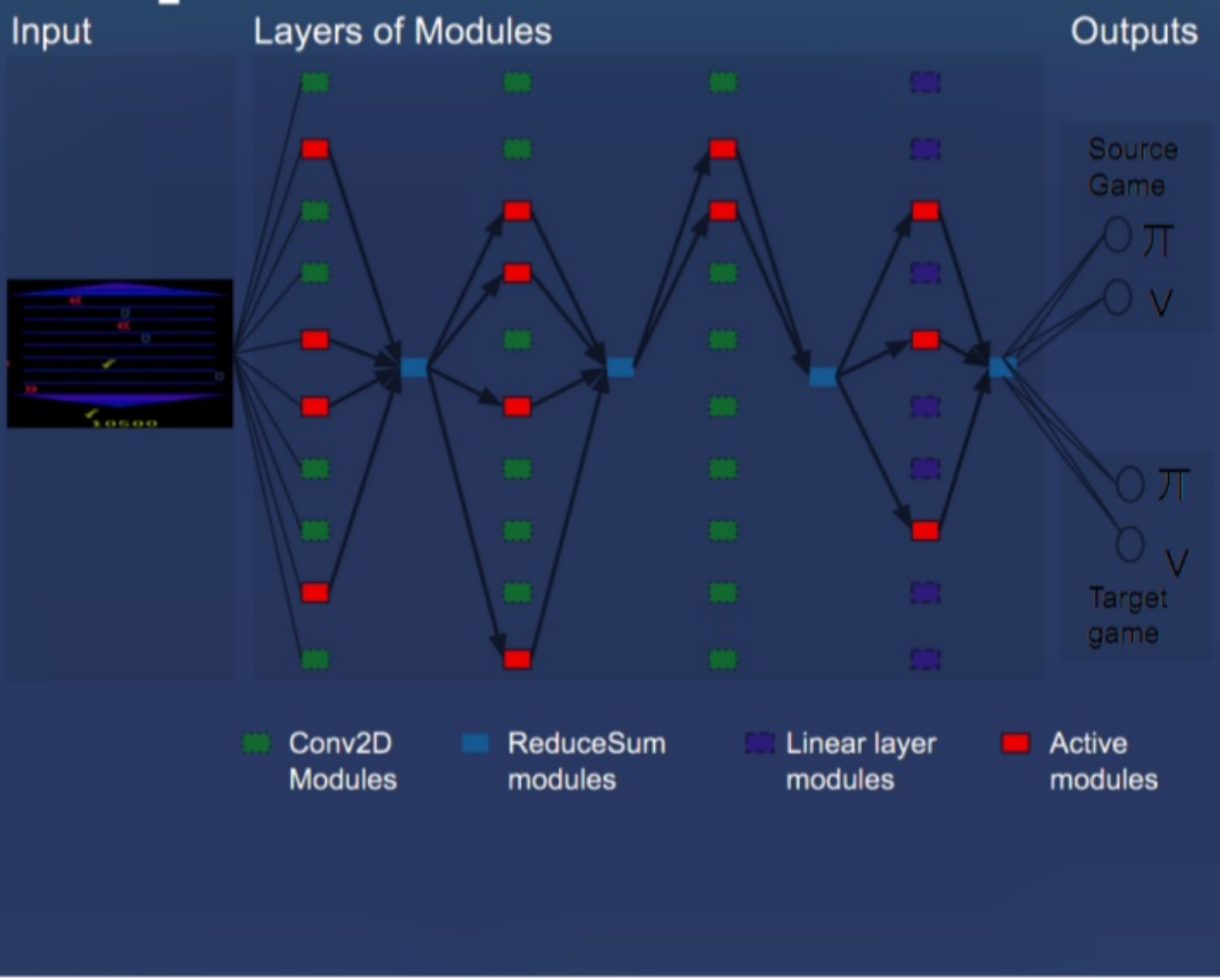

Towards AGI

OpenCog

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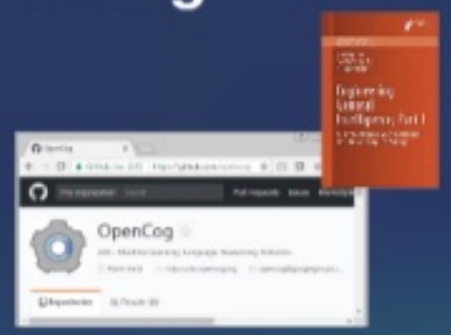

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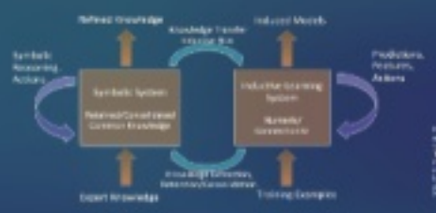

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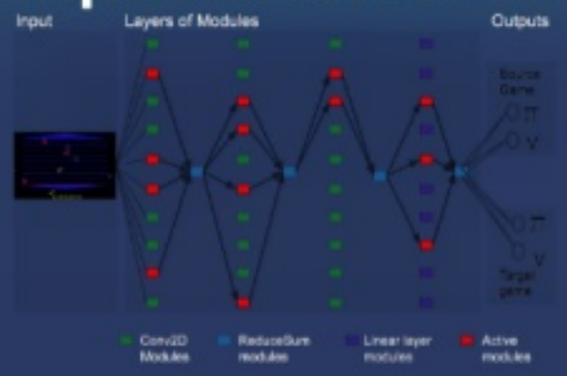

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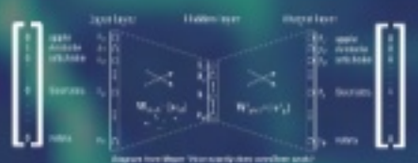

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Towards AGI

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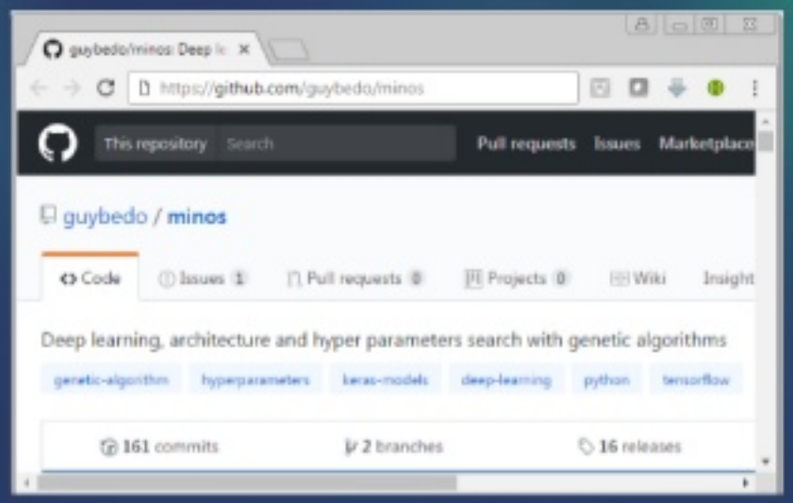
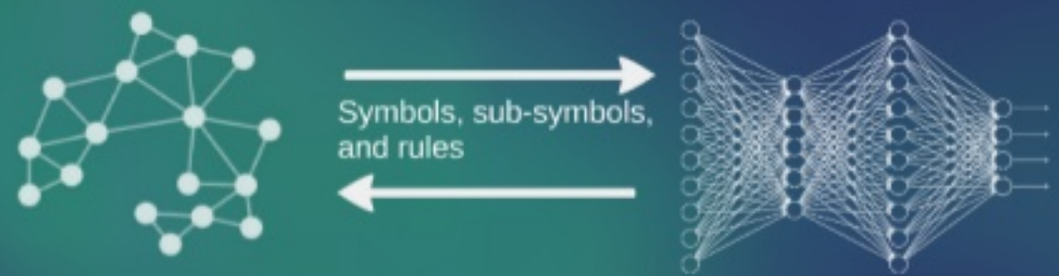
Minos



Symbolic Injection & Extraction



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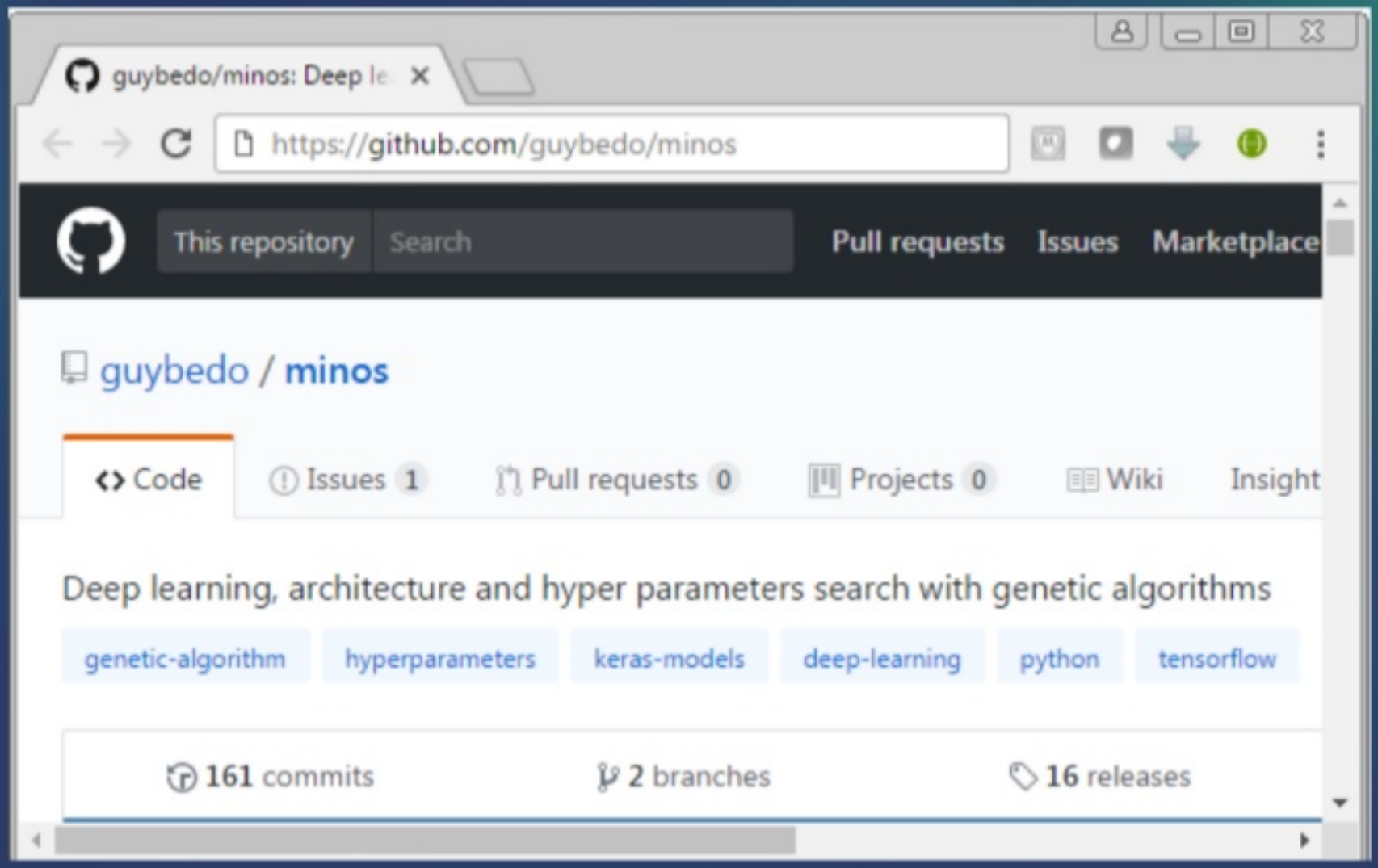
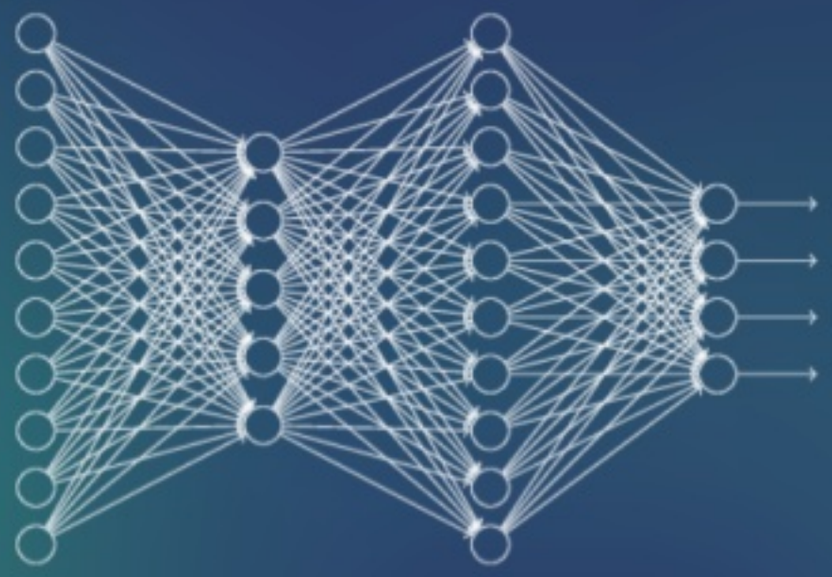

guybedo/minos: Deep le
https://github.com/guybedo/minos
This repository
Search
Pull requests
Issues
Marketplace
guybedo / minos
Code
Issues 1
Pull requests 0
Projects 0
Wiki
Insight
Deep learning, architecture and hyper parameters search with genetic algorithms
genetic-algorithm
hyperparameters
keras-models
deep-learning
python
tensorflow
161 commits
2 branches
16 releases

Symbolic Injection & Extraction

Symbols, sub-symbols, and rules



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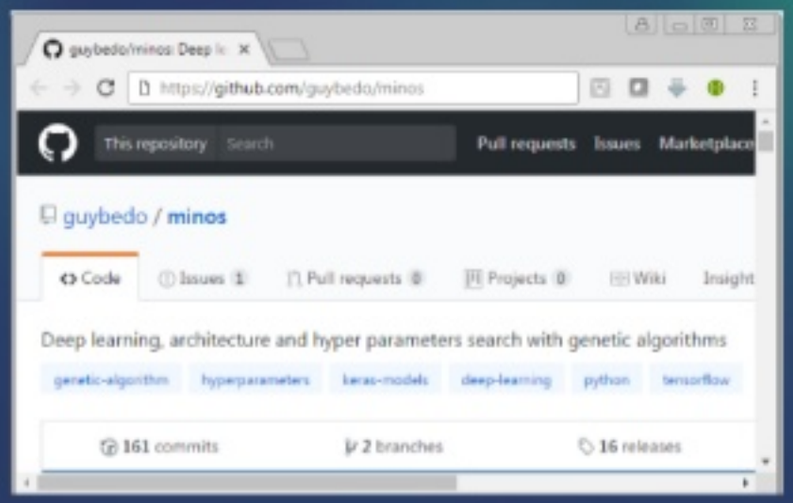

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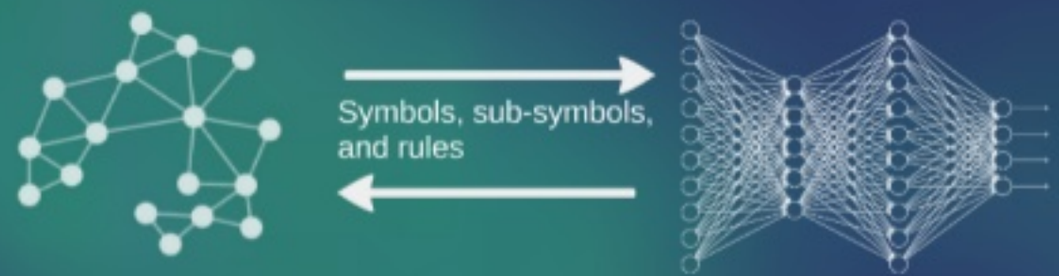

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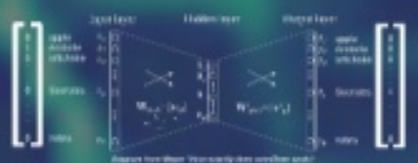

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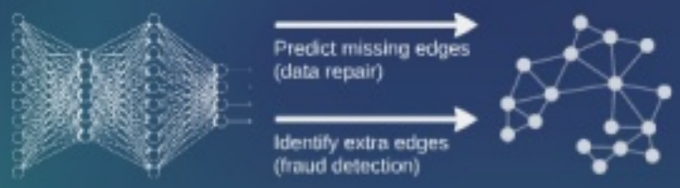
Neural predicts for knowledge graph



Neural-guided search

Other techniques/use cases:

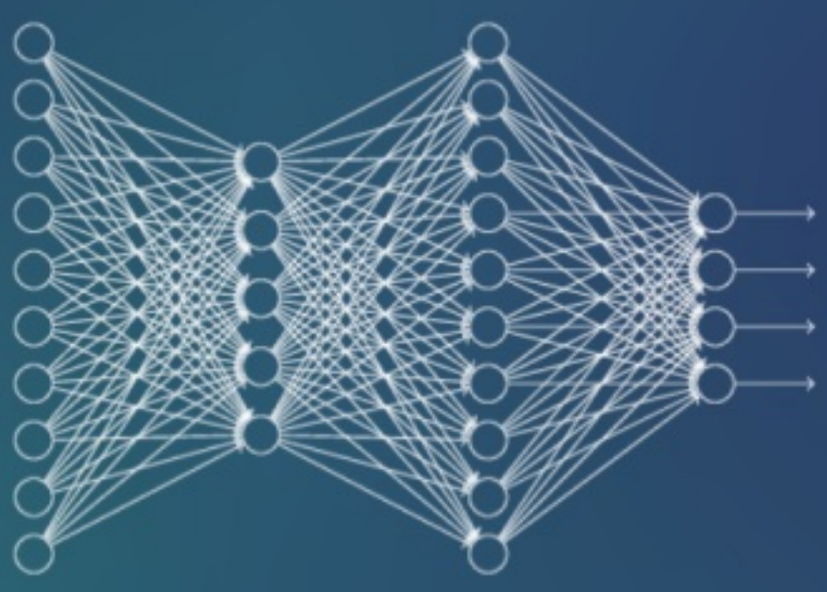
- Pharmaceutical compound generation
- Neural Theorem Provers (NTP)
- Optimization of constraints

Knowledge Graph Embedding

Image from Feng et al "Knowledge Graph Embedding by Flexible Translation"

- Encode graph relations as vectors
- Convenient input to neural networks

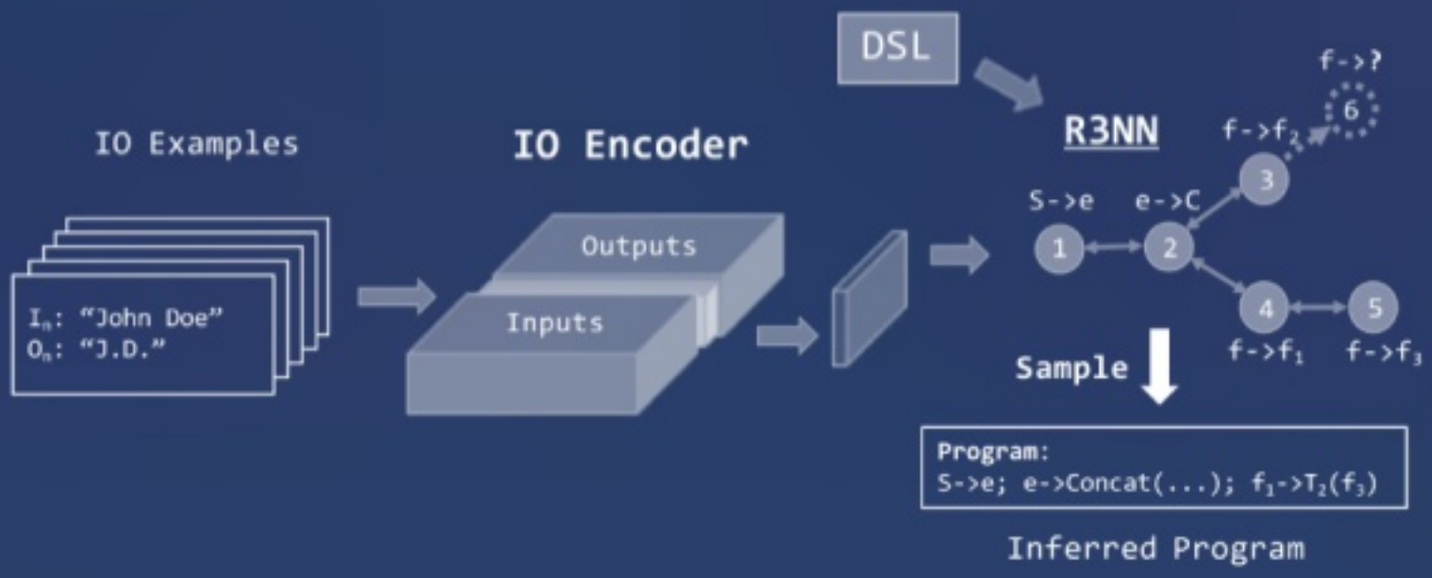
Neural predicts for knowledge graph



Predict missing edges
(data repair)

Identify extra edges
(fraud detection)

Neural-guided search



Deep API Programmer: Learning to Program with APIs

Surya Bhupatiraju
MIT
surya@mit.edu

Rishabh Singh
Microsoft Research
risin@microsoft.com

Abdel-rahman Mohamed
Microsoft Research
asamir@microsoft.com

Pushmeet Kohli
Microsoft Research
pkohli@microsoft.com

Abstract

We present DAPIP, a Programming-By-Example system that learns to program with APIs to perform data transformation tasks. We design a domain-specific language (DSL) that allows for arbitrary concatenations of API outputs and constant strings. The DSL consists of three family of APIs: regular expression-based APIs, lookup APIs, and transformation APIs. We then present a novel neural synthesis algorithm to search for programs in the DSL that are consistent with a given set of examples.

a domain-specific language (DSL), and then develop algorithms based on version-space algebra (VSA) [Polozov and Gulwani, 2015; Lau *et al.*, 2003] to efficiently search the space of programs. There are two key shortcomings of these approaches. First, the DSL is limited to only certain low-level *syntactic* regular expression-based operators that allow for an efficient structuring of search space. This limits the expressiveness of the PBE systems; for example, they do not allow *semantic* data transformations using arbitrary transformation functions such as obtaining month names from a date or abbreviating the state name in an input address. Second, building an efficient synthesizer using VSA requires a large

Other techniques/use cases:

- Phamaceutical compound generation
- Neural Theorem Provers (NTP)
- Optimization of constraints

Knowledge Graph Embedding

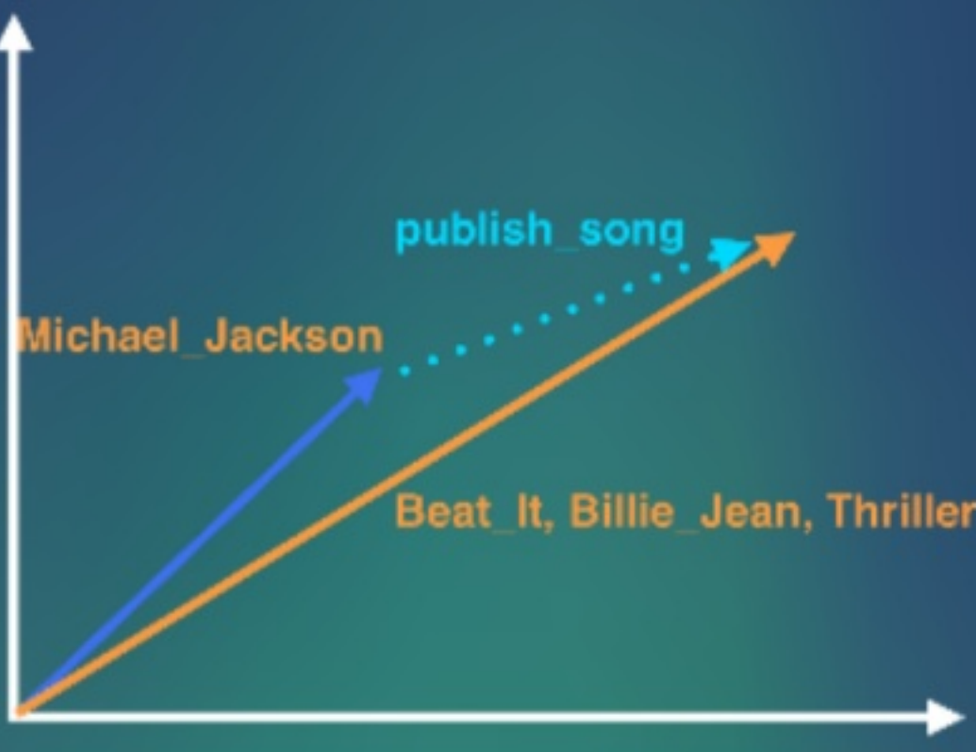
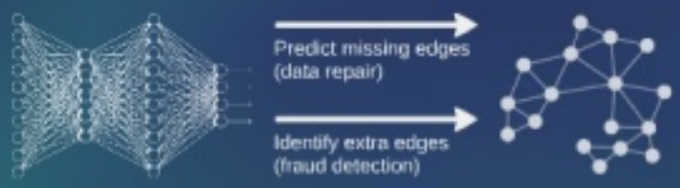


Image from Feng et al "Knowledge Graph Embedding by Flexible Translation"

- Encode graph relations as vectors
- Convenient input to neural networks

Enhance symbolic with neural

Neural predicts for knowledge graph



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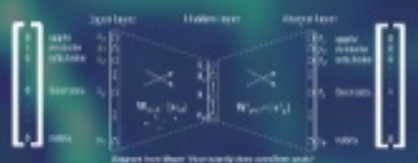
Examples

word2vec



- From corpus of sentences, train neural network to predict next word in sentence

Towards AGI

Enhance neural with symbolic

Enhance symbolic with neural

Pipelines

Understanding

- Explaining the "black box" of a neural network

- Transfer Learning
  - One-Shot Learning

Pipelines

Sequence-to-Sequence

Story Summarization

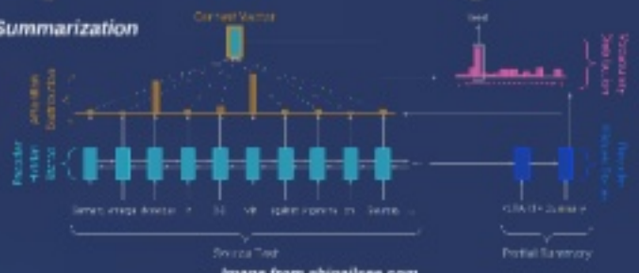


Image from abigailsee.com

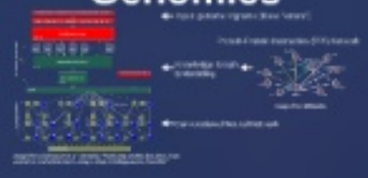
Other techniques/use cases:
- Human language translation
- Code generation from natural language requirements

Sequence-to-Class

NLP

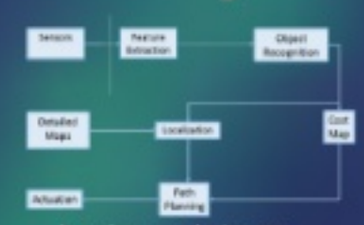
- Sentiment Analysis
- Parsing

Genomics



Neural-to-Symbolic

- Self-Driving Cars



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- Computer Vision
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Sequence-to-Sequence

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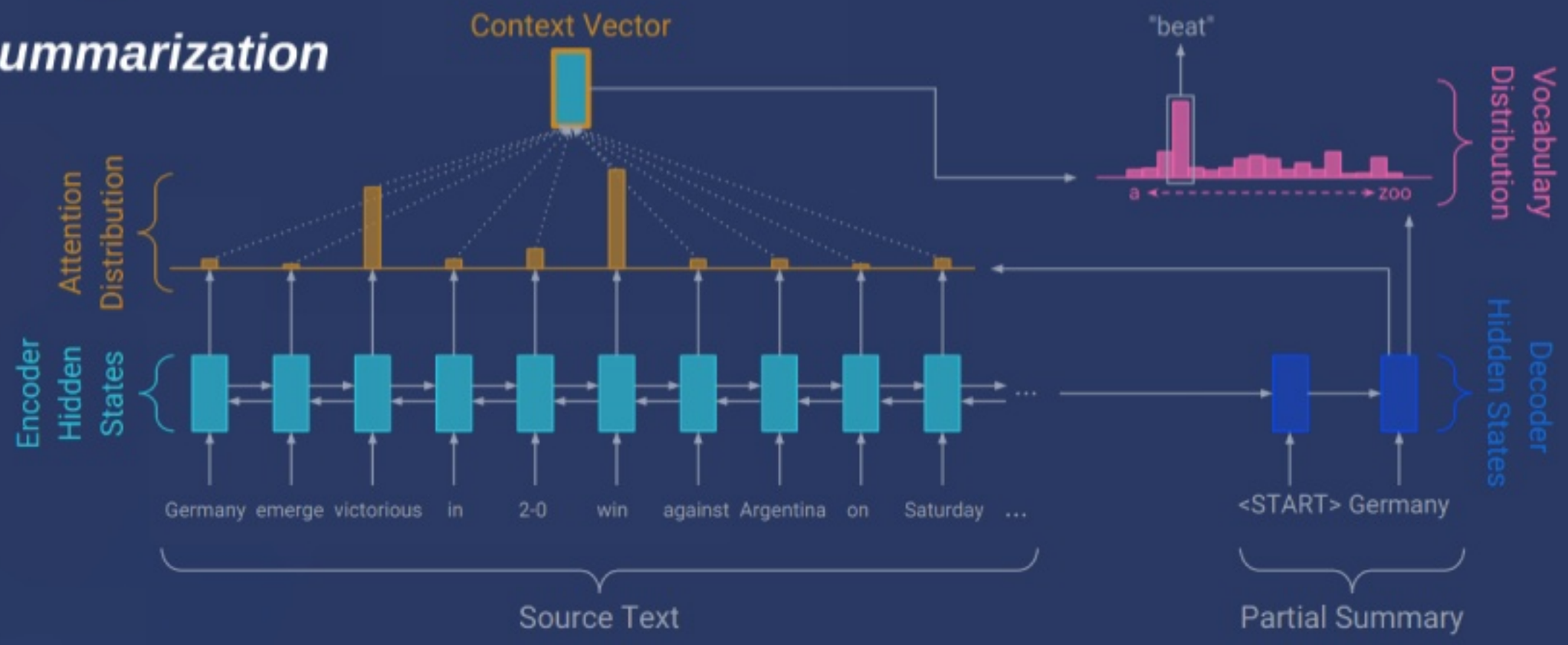

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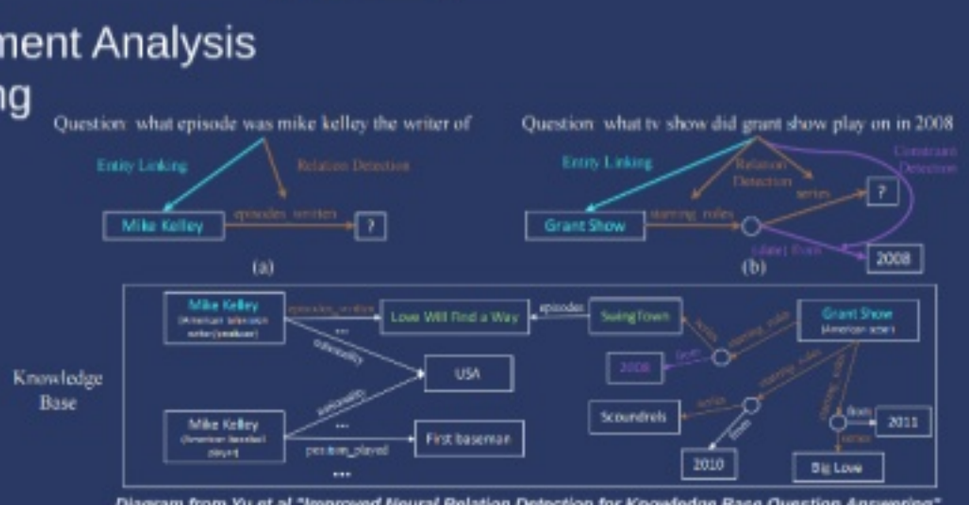

Diagram from Yu et al "Improved Neural Relation Detection for Knowledge Base Question Answering"

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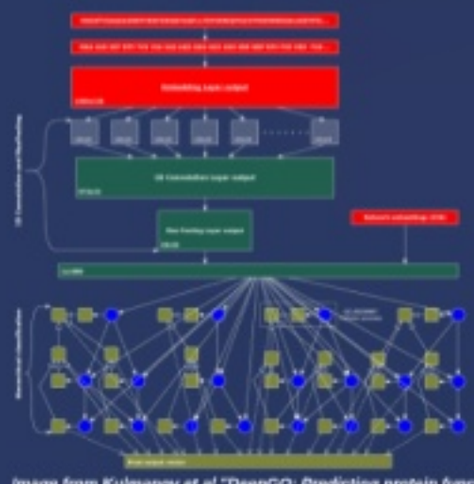

← Input: genome trigrams (three "letters")

← Convolutional Neural Network

Image from Kulmanov et al "DeepGO: Predicting protein functions from sequence and interactions using a deep ontology-aware classifier"

Protein-Protein Interaction (PPI) Network

← Knowledge Graph Embedding

Image from Wikipedia

NLP

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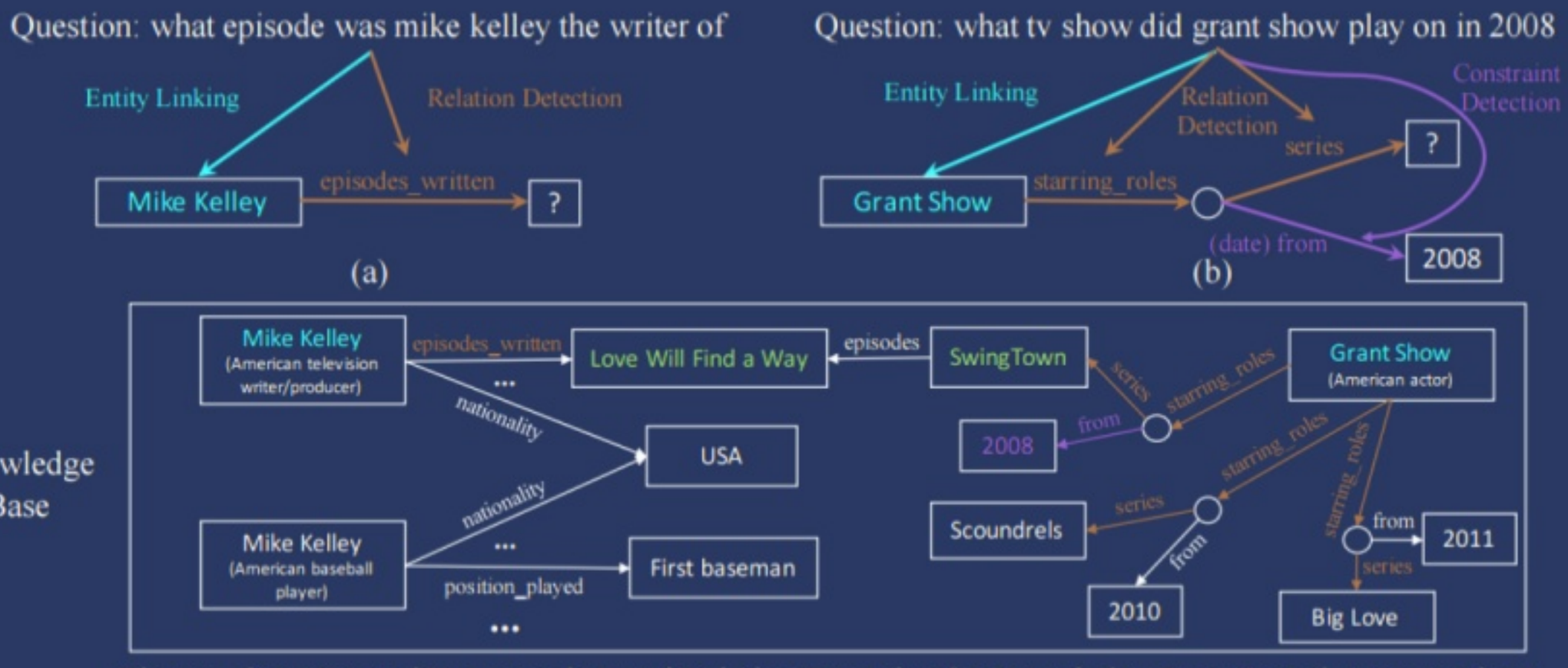

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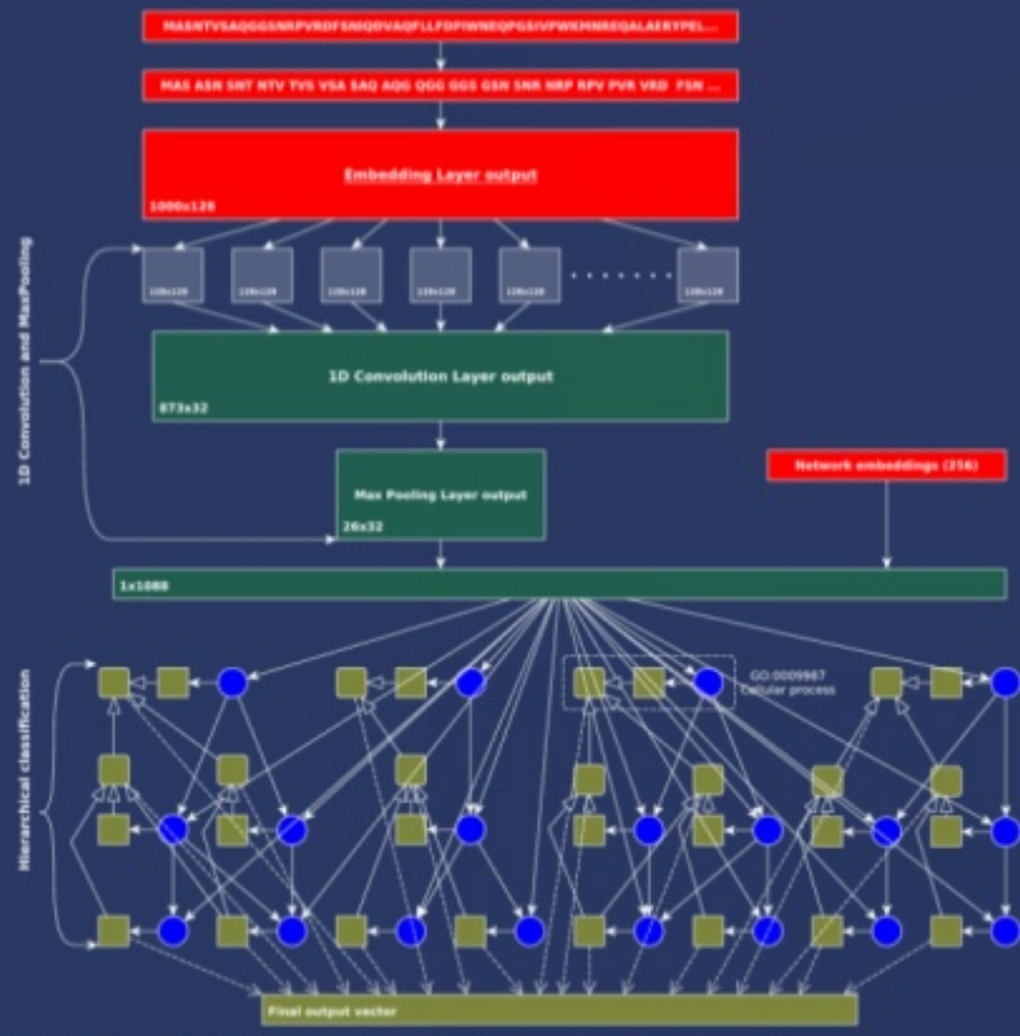

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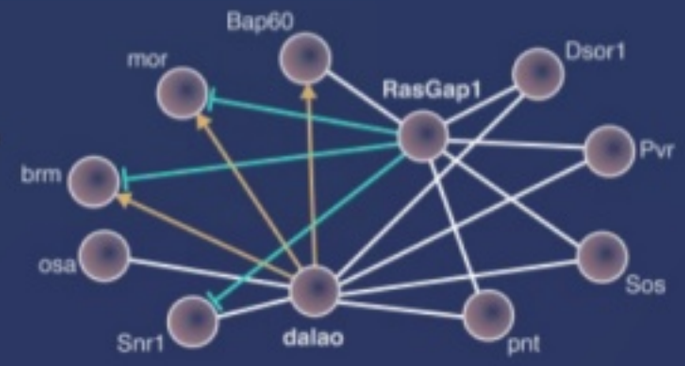

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Sequence-to-Class

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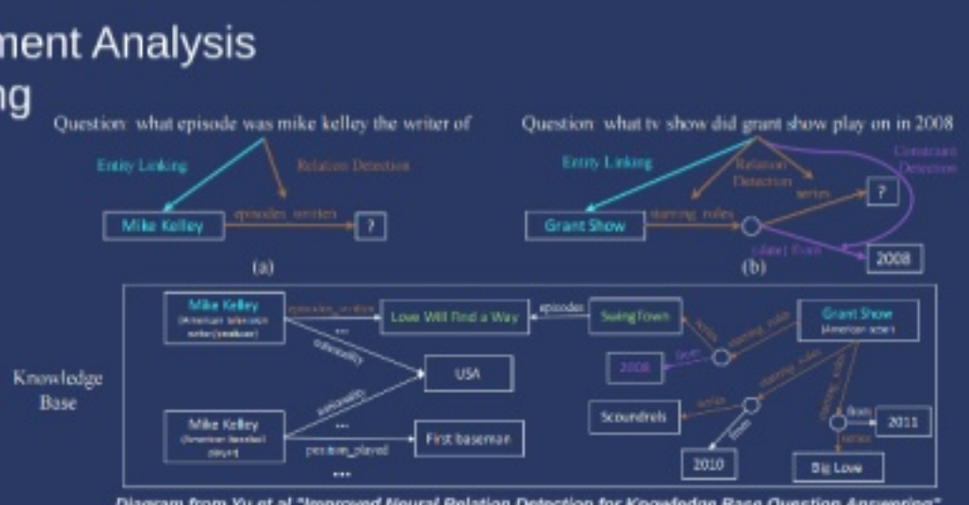

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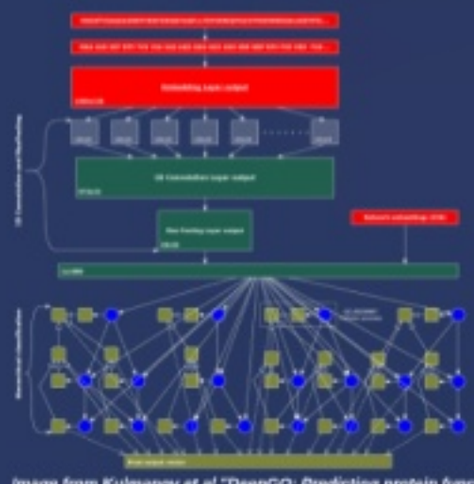

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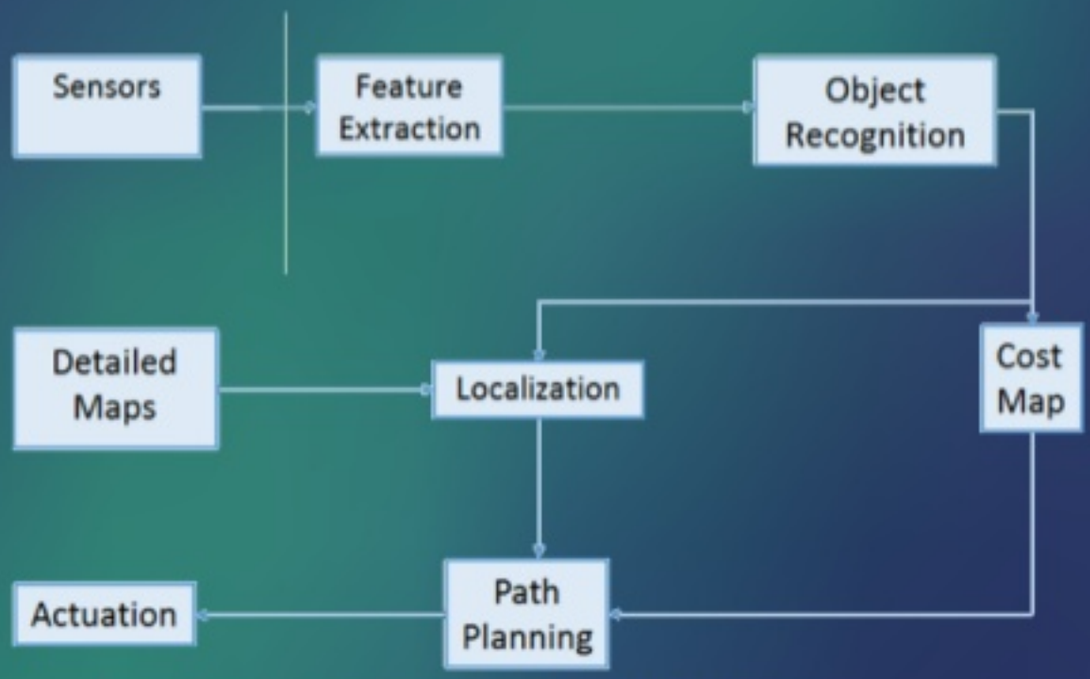

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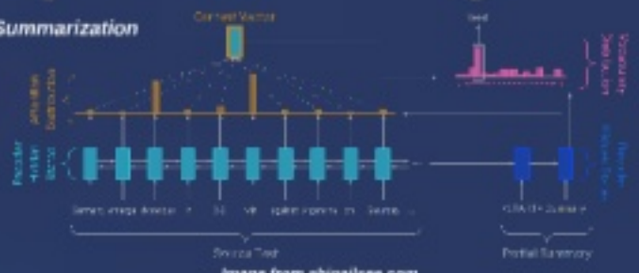

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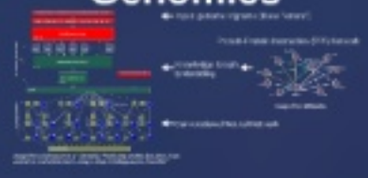

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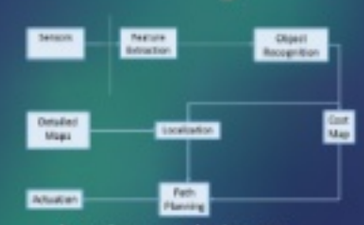

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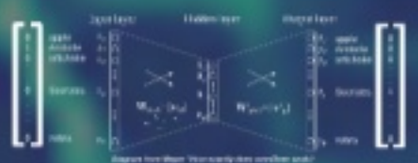
Examples

word2vec



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Towards AGI

Enhance neural with symbolic

Enhance symbolic with neural

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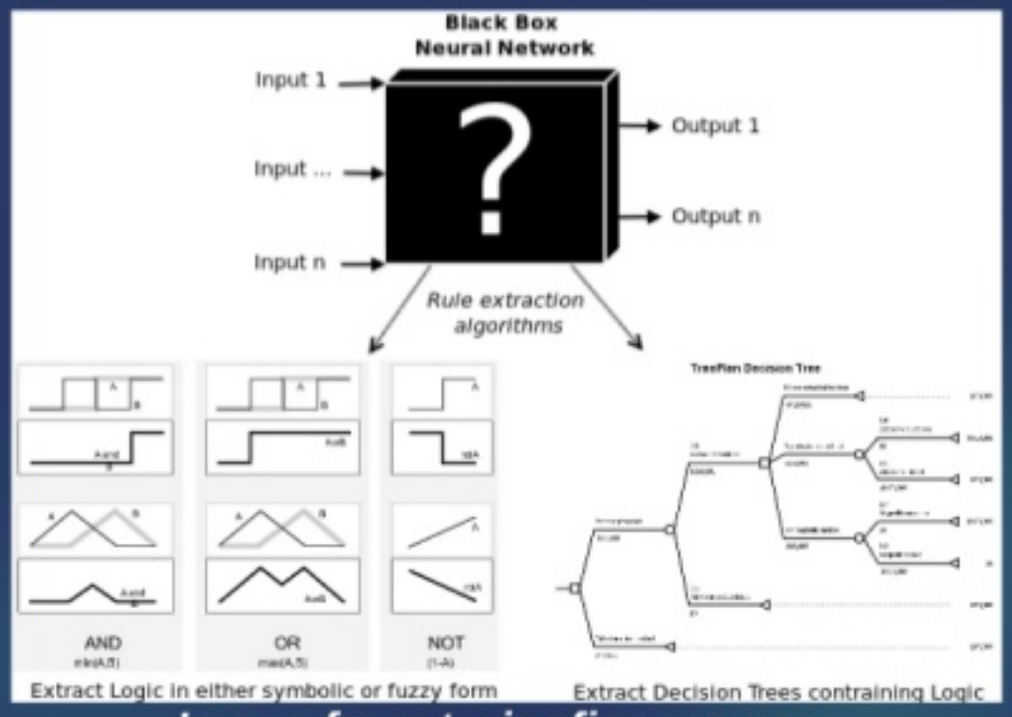

Image from turingfinance.com

- Transfer Learning
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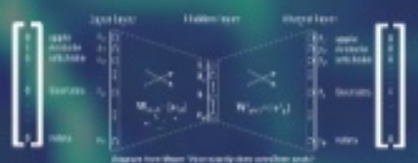
Examples

word2vec



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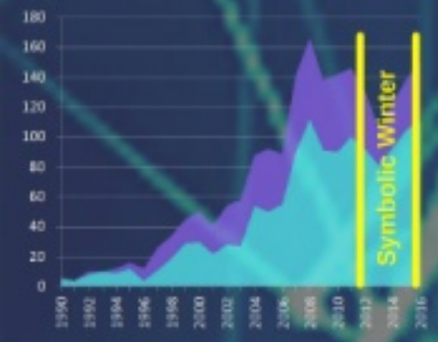
What It's Not

- All systems have symbols as input and output
- LSTM (long short-term memory)
- NTM (Neural Turing Machines)

Neuro-Symbolic

Trends



- Chart approximate
- Some papers contain both terms
- Some contain term only in references
- Some papers are on cognitive psychology

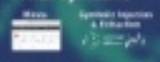
- Infrequently used term NSI: Neural Symbolic Integration

Examples

word2vec

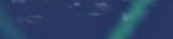
Towards AGI

Enhance neural with symbolic



Enhance symbolic with neural

Pipelines



Understanding

What It's Not

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- NTM (Neural Turing Machines)

Philosophy

What is AI?

Weak AI

Classic AI

Strong AI

Artificial General Intelligence (AGI)

Artificial Super Intelligence (ASI)

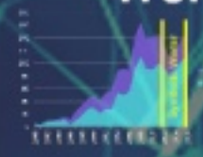
It's OK to say "AI" now

AI Permadrost

Silicon Valley AI Depts

Neuro-Symbolic

Trends



Examples

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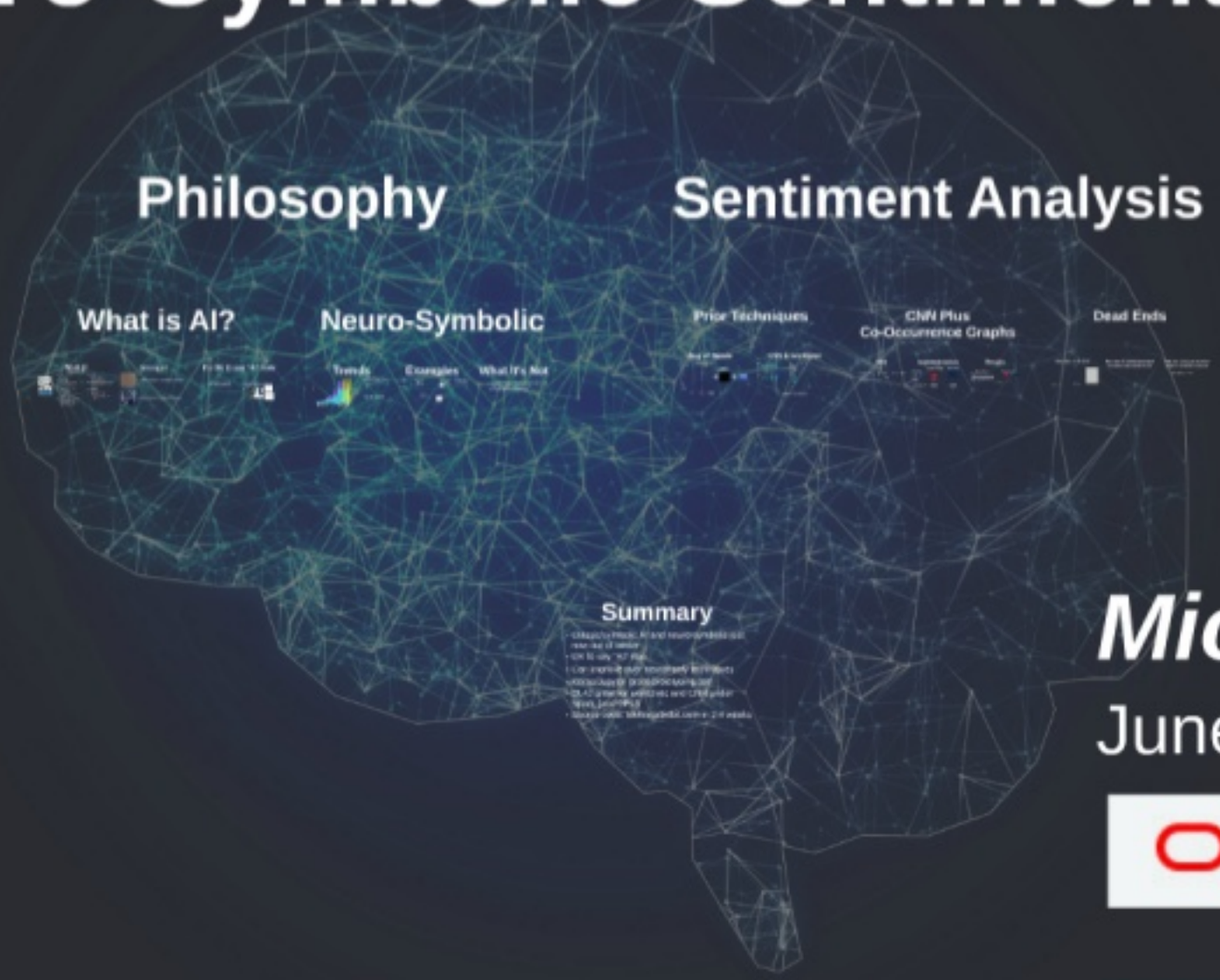
Neuro-Symbolic Sentiment Analysis



SPARK SUMMIT 2017

Michael Malak

June 7, 2017

ORACLE Cloud

Big Data Preparation

Analytics Cloud

Sentiment Analysis

Prior Techniques

Bag of Words

CNN & word2vec

CNN Plus Co-Occurrence Graphs

Idea

Implementation

Results

Dead Ends

Bad idea #1: 2D CNN

Bad idea #2: Semi-Supervised Learning of good/bad words

Bad idea #3: Co-occurrence graph to identify unigrams

Prior Techniques

Bag of Words

CNN & word2vec

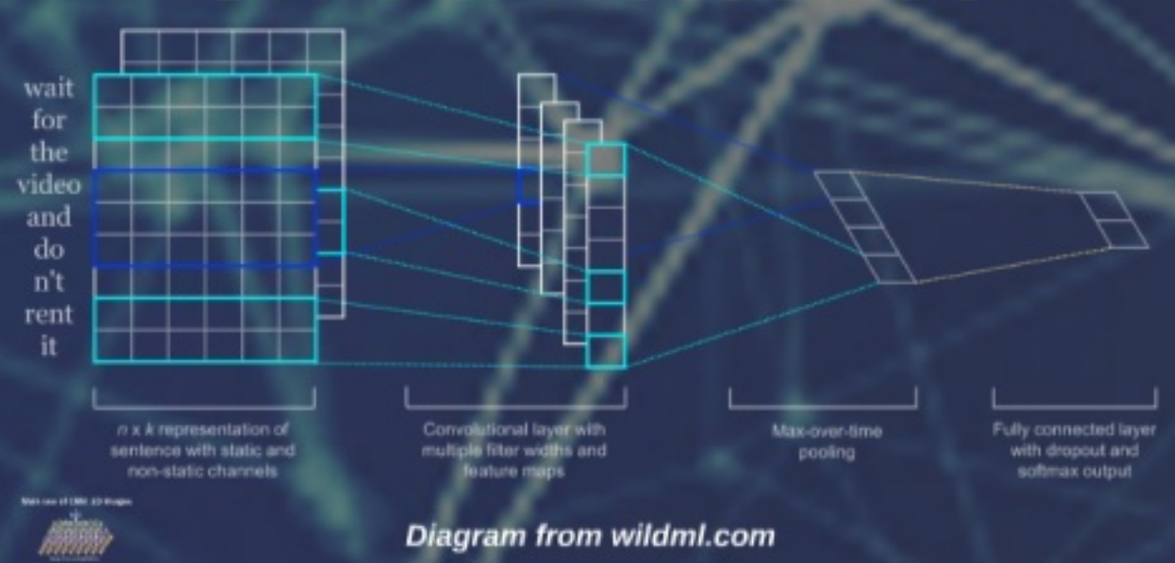


Diagram from wildml.com

Bag of Words

Dictionary

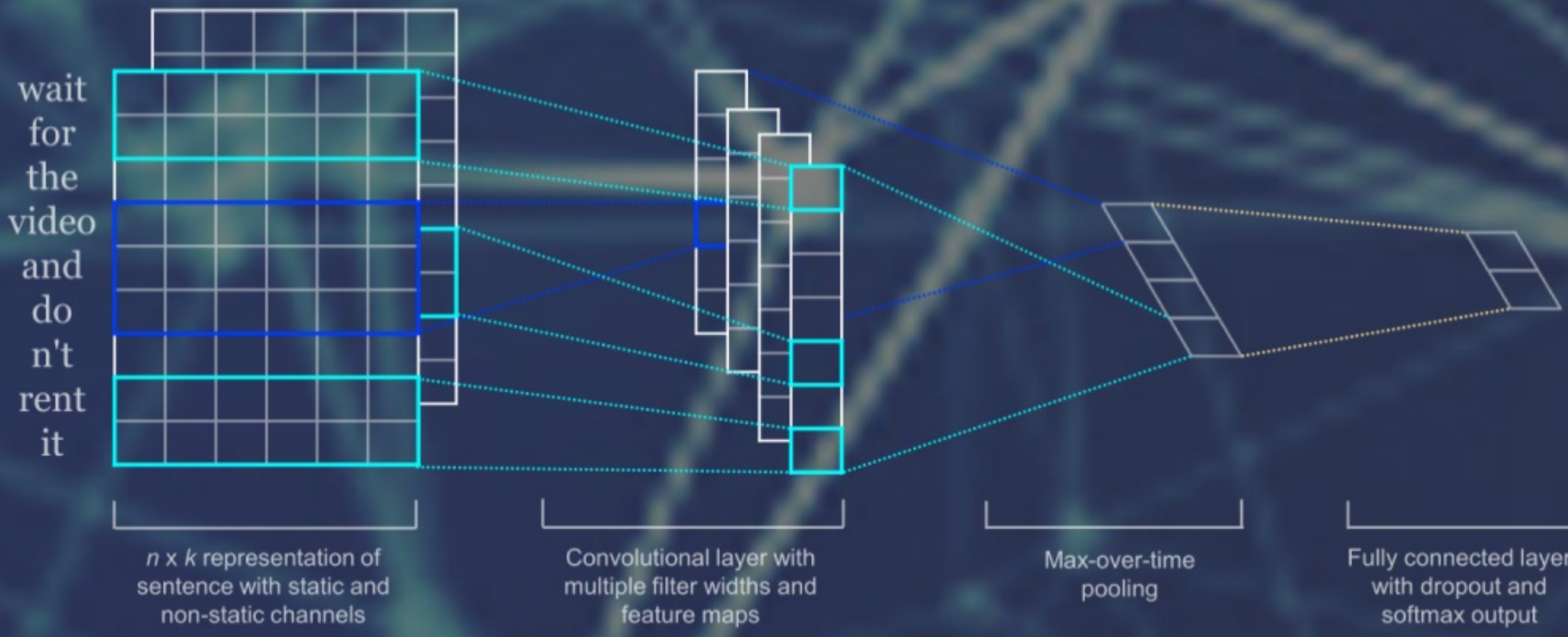
	"The film is the best"	"The film stinks"
The	2	1
film	1	1
is	1	1
best	1	0
stinks	0	1
	Pos	Neg

Labels

Logistic Regression

Model

CNN & word2vec



Main use of CNN: 2D Images

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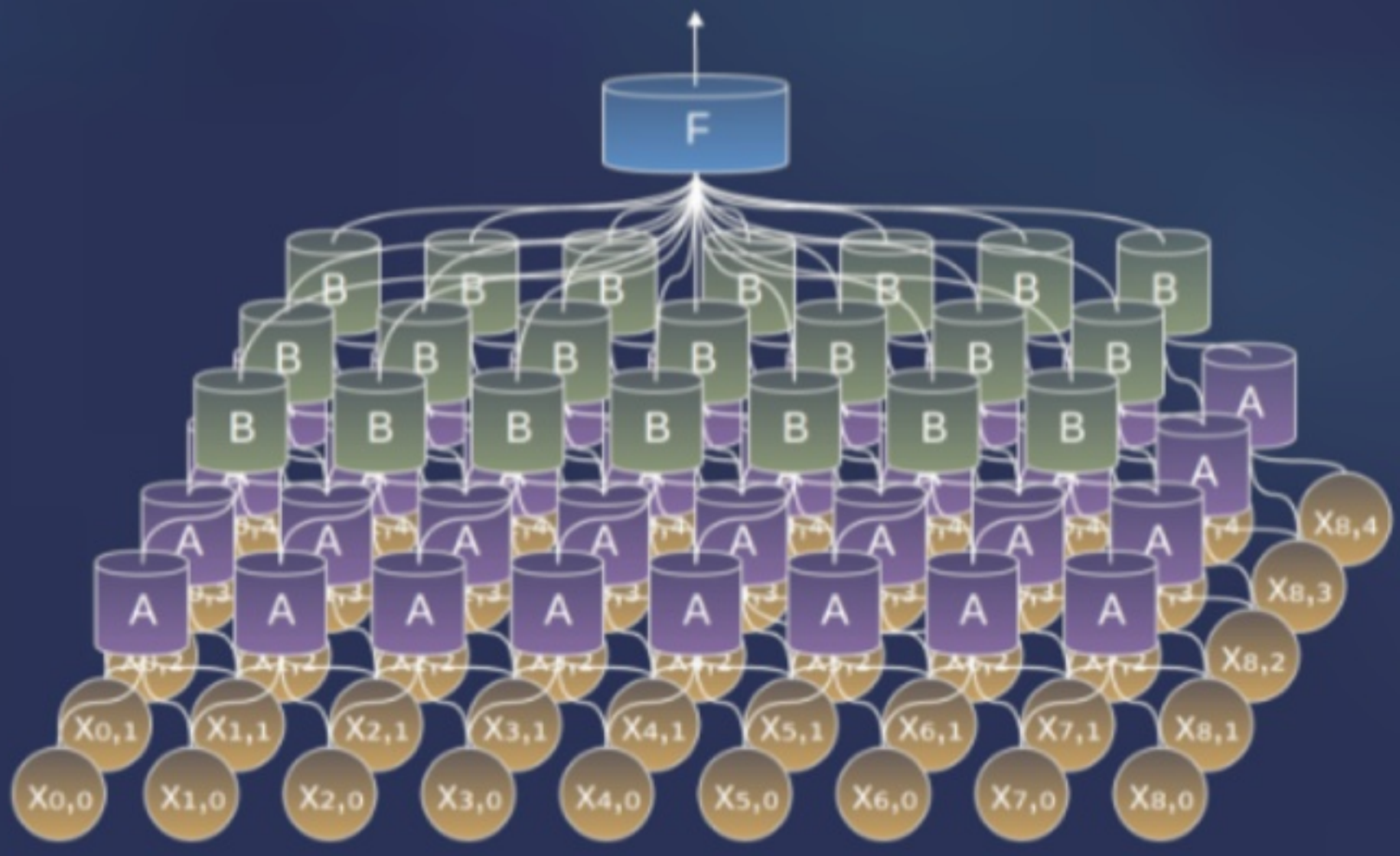
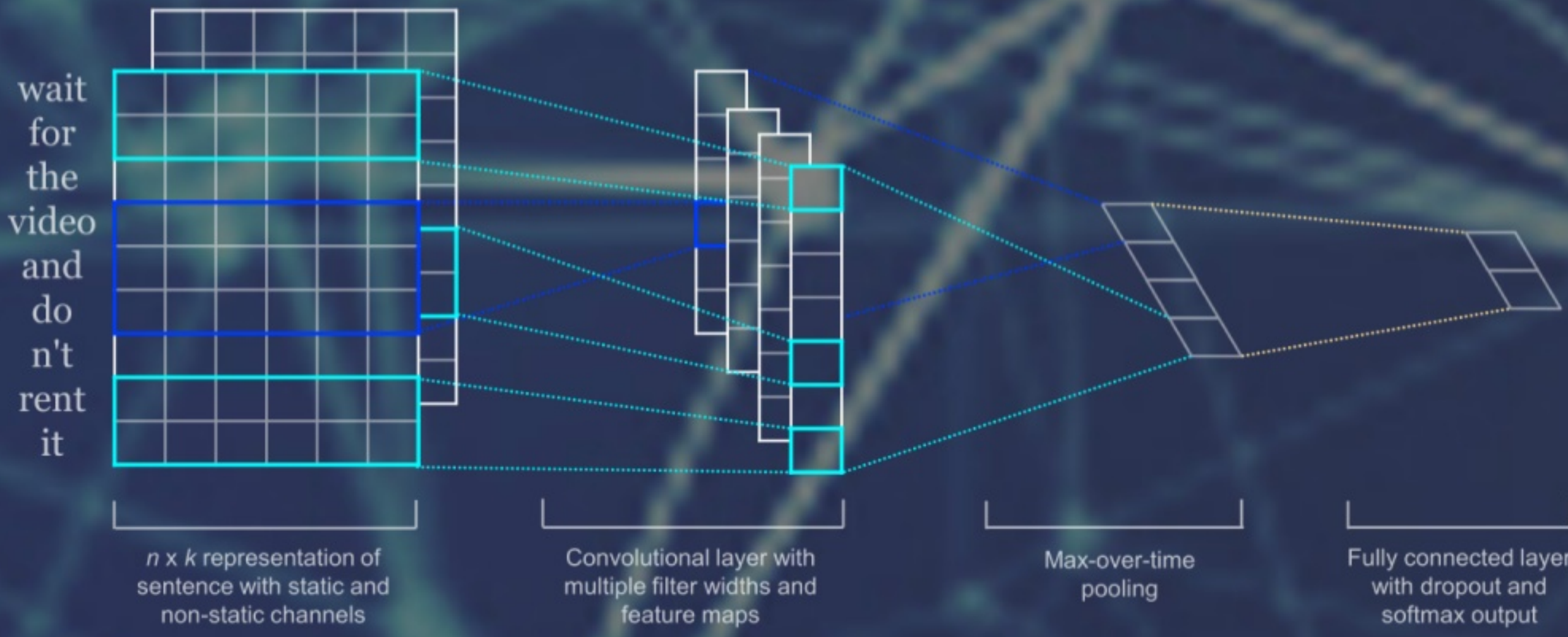


Image from colah.github.io

CNN & word2vec



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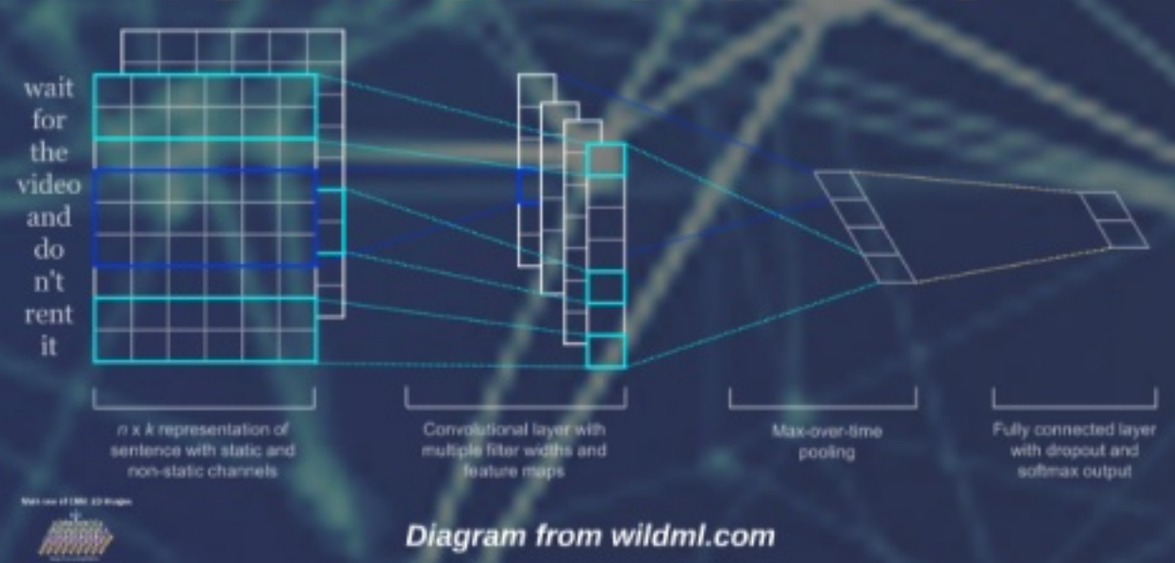
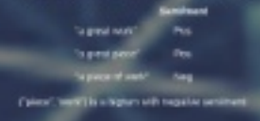


Diagram from wildml.com

CNN Plus Co-Occurrence Graphs

Idea

Bigrams carry context



Find bigrams with GraphX

Incorporating bigrams

Implementation

	Jupyter/Python	*Spark/Scala*
word2vec	gensim	DL4J
CNN	Keras	DL4J
Graph	Adjacency matrix	GraphX
stop words	NLTK	NLTK

Results

Data Used

Data Source

Data Prep

Accuracy

Idea

Bigrams carry context

	Sentiment
"a great work"	Pos
"a great piece"	Pos
"a piece of work"	Neg

("piece","work") is a bigram with negative sentiment

Find bigrams with GraphX

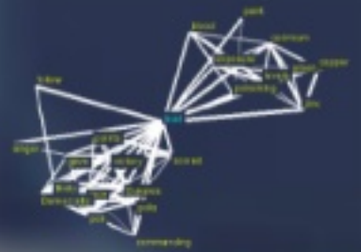


Diagram from Richter et al "Exploiting the leipzig corpora collection"

- If two words appear near each other in the training corpus, draw an edge
- (or increment edge count if there is already an edge)
- Edges with high count are the important bigrams to track

Incorporating bigrams

	word2vec vectors (300 columns)				bigram presence indicators (300 columns)			
The	0.3	0.5	⋯	0.1	0	0	⋯	0
film	0.6	0.2	⋯	0.2	0	0	⋯	0
is	0.1	0.1	⋯	0.0	0	0	⋯	0
a	0.9	0.3	⋯	0.5	0	0	⋯	0
piece	1.0	0.6	⋯	0.4	1	0	⋯	0
of	0.9	0.4	⋯	0.4	1	0	⋯	0
work	0.7	0.9	⋯	0.1	1	0	⋯	0

("great","film")

("piece","work")

Bigrams carry context

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of	0.9	0.4	…	0.4	**1**	0	…	0
work	0.7	0.9	…	0.1	**1**	0	…	0

("great", "film")
("piece", "work")

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"a great piece"	Pos
"a piece of work"	Neg

("piece","work") is a bigram with negative sentiment

Find bigrams with GraphX

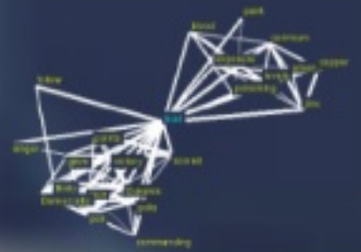


Diagram from Richter et al "Exploiting the leipzig corpora collection"

- If two words appear near each other in the training corpus, draw an edge
- (or increment edge count if there is already an edge)
- Edges with high count are the important bigrams to track

Incorporating bigrams

	word2vec vectors (300 columns)				bigram presence indicators (300 columns)			
The	0.3	0.5	⋯	0.1	0	0	⋯	0
film	0.6	0.2	⋯	0.2	0	0	⋯	0
is	0.1	0.1	⋯	0.0	0	0	⋯	0
a	0.9	0.3	⋯	0.5	0	0	⋯	0
piece	1.0	0.6	⋯	0.4	1	0	⋯	0
of	0.9	0.4	⋯	0.4	1	0	⋯	0
work	0.7	0.9	⋯	0.1	1	0	⋯	0

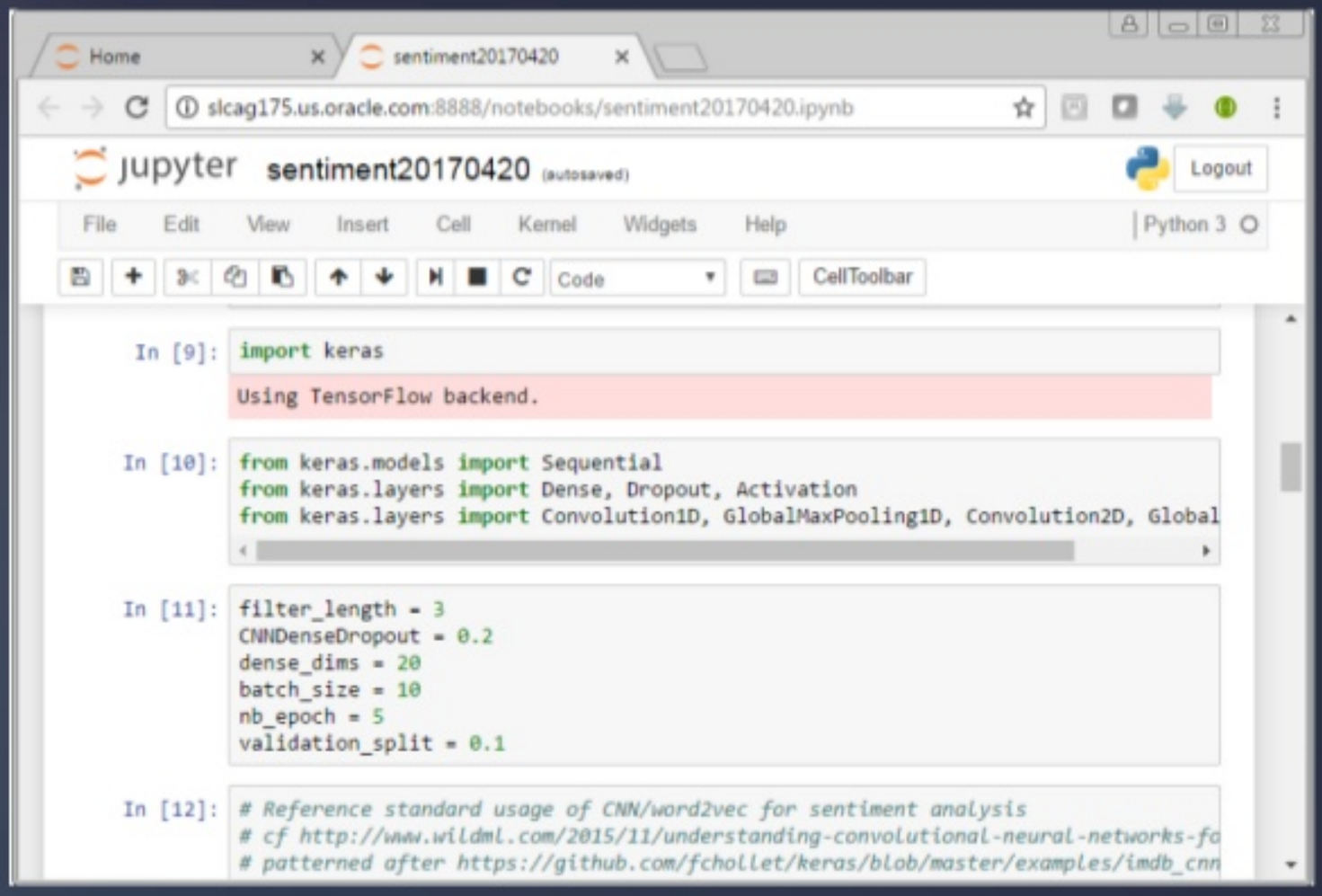
("great","film")

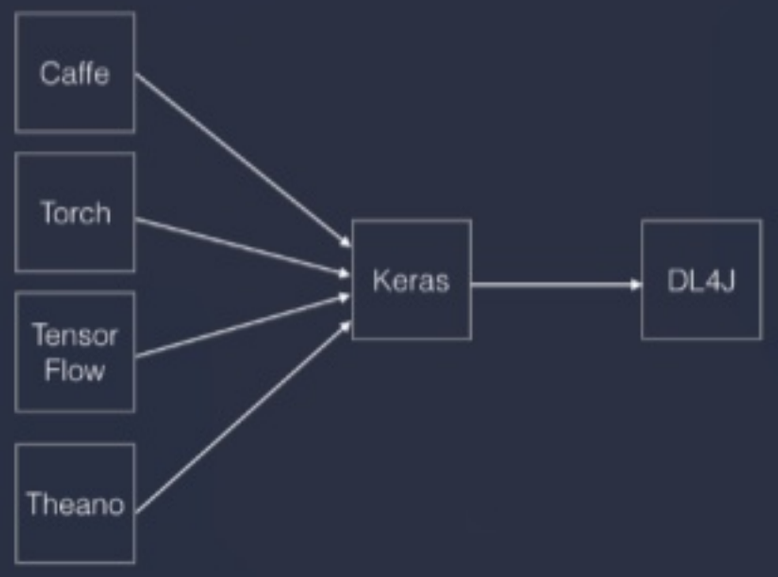
("piece","work")

Implementation

word2vec	gensim	DL4J DEEPLEARNING4J
Jupyter/Python 		*Spark/Scala*
CNN	Keras	DL4J DEEPLEARNING4J 
Graph	Adjacency matrix 	GraphX
stop words 	NLTK	NLTK

Prototype in Jupyter/Python, Implement in Spark/Scala





org.deeplearning4j.nn.modelimport.keras

Class KerasModelImport

DL4J can import Keras model (to predict in Spark), but not pipeline (to train & predict in Spark)

Implementation

word2vec	gensim	DL4J DEEPLEARNING4J
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Spark/Scala

DL4J

DEEPLEARNING4J

DL4J

DEEPLEARNING4J

word2vec on Spark techology choice

Spark MLlib

- SPARK-15328
- "Word2Vec import for original binary format"
- Unresolved
- PR #13735
- Doesn't work either

DL4J DEEPLEARNING4J

- Works

Neither distributes the model (1.5GB raw data)

CNN on Spark tehnology choice

SparkPackages

mCNN

github.com/hhbyyh/SparkCNN

DL4J DEEPLEARNING4J

- Supports Spark, GPU
- Compared to Keras:

word2vec on Spark techology choice

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DL4J Word2Vec API Gotcha

Neither distributes the model (1.5GB raw data)

DL4J Word2Vec API Gotcha

readWord2VecModel

```
public static Word2Vec readWord2VecModel(java.lang.String path)
```

This method 1) Binary model, either compressed or not. Like well-known Google Model 2) Popular CSV word2vec text format 3) DL4j compressed format Please note: Only weights will be loaded by this method.

loadGoogleModelNonNormalized

```
@Deprecated
public static WordVectors loadGoogleModelNonNormalized(java.io.File modelFile,
                                                       boolean binary,
                                                       boolean lineBreaks)
                                                throws java.io.IOException
```

Deprecated.

Loads the Google model without normalization being applied. PLEASE NOTE: Use this method only if you understand why you need not-normalized model. In all other cases please use loadGoogleModel() instead. Deprecation note: Please, consider using readWord2VecModel() or loadStaticModel() method instead

word2vec on Spark techology choice

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DEEPLEARNING4J

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DL4J

DEEPLEARNING4J

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- 0.5
- Pooling layers under development
- No check-ins for 2 years

DL4J
DEEPLEARNING4J

- Supports Spark, GPU
- Compared to Keras:
  - Do your own train/test split
  - Do your own batching
  - More parameters, more tweaking
- Dependency on ND4J for BLAS
- Has its own API, learning curve

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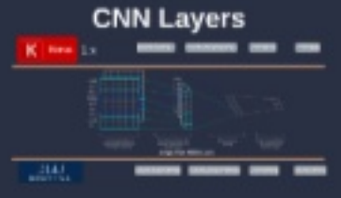

CNN Layers

Keras 1.x

`Convolution1D` `GlobalMaxPooling1D` `Dense(20)` `Dense(1)`

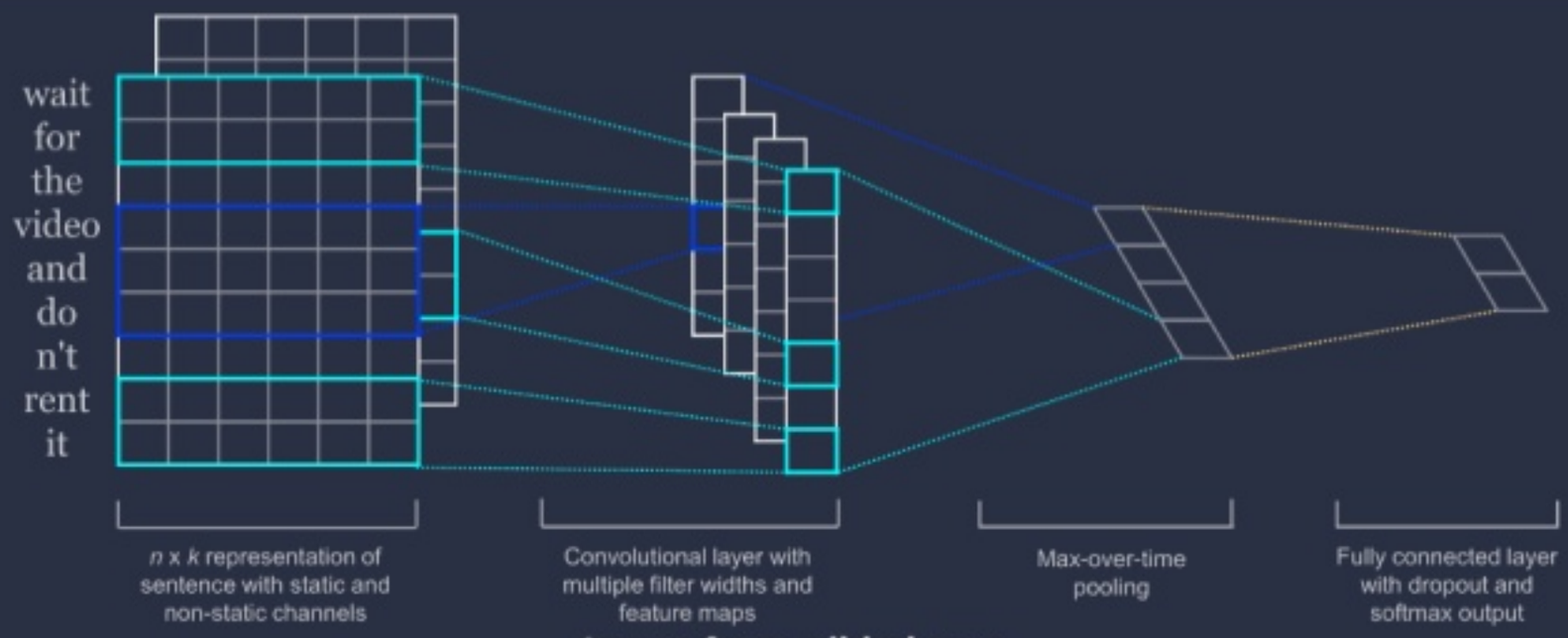

Image from wildml.com

DL4J
DEEPLEARNING4J

`ConvolutionLayer` `GlobalPoolingLayer` `DenseLayer` `OutputLayer`

CNN on Spark tehnology choice

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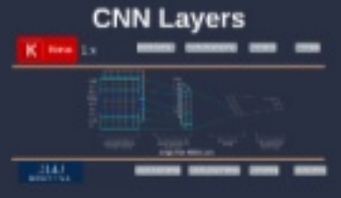

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Graph	Adjacency matrix 	GraphX
stop words 	NLTK	NLTK

Graphs in Python Technology Choice

SciPy.org

scipy.sparse.csgraph

NetworkX

	1	2	3	4	5	6
1	0	1	1	0	0	0
2	1	0	0	1	0	0
3	1	0	0	1	0	0
4	0	1	1	0	1	0
5	0	0	0	1	0	1
6	0	0	0	0	1	0

Adjacency Matrix

Some Graph Philosophy

- Graphs are isomorphic to matrices
- Efficient if a lot of "missing" edges
- Edge weights escape binary edge/no-edge

Implementation

word2vec	gensim	DL4J DEEPLEARNING4J
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Graph

stop words

Usage of Stop Words

- From NLTK, just read directly from nltk_data/stopwords.zip/stopwords/english
- 153 words
- Used for bigram detection (co-occurrence graph) but not for stacking the word2vec vectors for the CNN input matrix

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- 153 words
- Used for bigram detection (co-occurrence graph) but not for stacking the word2vec vectors for the CNN input matrix

```
['i',
 'me',
 'my',
 'myself',
 'we',
 'our',
 'ours',
 'ourselves',
 'you',
 'your',
 'yours',
 'yourself',
 'yourselves',
 'he',
 'him',
 'his',
 'himself',
 'she',
 'her',
```

Implementation

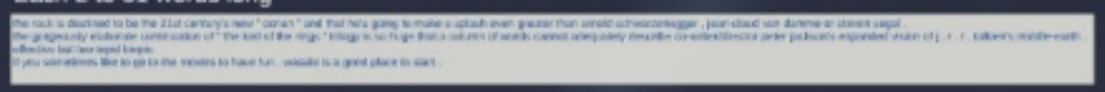
word2vec	gensim	DL4J DEEPLEARNING4J
Jupyter/Python 		*Spark/Scala*
CNN	Keras	DL4J DEEPLEARNING4J 
Graph	Adjacency matrix 	GraphX
stop words 	NLTK	NLTK

Results

Data Used

Data Source

- Cornell movie review data
- http://www.cs.cornell.edu/people/pabo/movie-review-data/
- 5,331 positive reviews, 5,331 negative reviews
- Each 2 to 51 words long



Data Prep

```
def readTweets(filename:String, isPositive:Boolean) = sc.makeRDD(
  Source.fromFile(filename)(Codec.UTF8.decoder.onMalformedInput(CodingErrorAction.IGNORE))
        .getLines.toList.map(x => ("[^a-zA-Z ]".r.replaceAllIn(x,"").split(" +"), isPositive)))
```

- Strip non-alpha
- Did not same-case

Accuracy

	Keras / jupyter	DL4J / Spark
CNN/word2vec	76%	68%
CNN/word2vec + co-occurrence graph	80%	70%

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Data Source

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- 5,331 positive reviews, 5,331 negative reviews
- Each 2 to 51 words long

the rock is destined to be the 21st century's new " conan " and that he's going to make a splash even greater than arnold schwarzenegger , jean-claud van damme or steven segal .
the gorgeously elaborate continuation of " the lord of the rings " trilogy is so huge that a column of words cannot adequately describe co-writer/director peter jackson's expanded vision of j . r . r . tolkien's middle-earth .
effective but too-tepid biopic
if you sometimes like to go to the movies to have fun , wasabi is a good place to start .

Data Prep

```
def readTweets(filename:String, isPositive:Boolean) = sc.makeRDD(
  Source.fromFile(filename)(Codec.UTF8.decoder.onMalformedInput(CodingErrorAction.IGNORE))
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```

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Accuracy

Keras

DL4J
DEEPLEARNING4J

jupyter

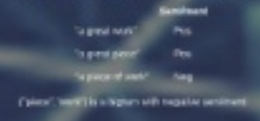
Spark

CNN/word2vec	76%	68%
CNN/word2vec + co-occurrence graph	80%	70%

CNN Plus Co-Occurrence Graphs

Idea

Bigrams carry context



Find bigrams with GraphX

Incorporating bigrams

Implementation

	Jupyter/Python	*Spark/Scala*
word2vec	gensim	DL4J
CNN	Keras	DL4J
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Results

Data Used

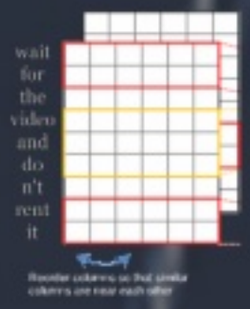
Data Source

Data Prep

Accuracy

Dead Ends

Bad idea #1: 2D CNN

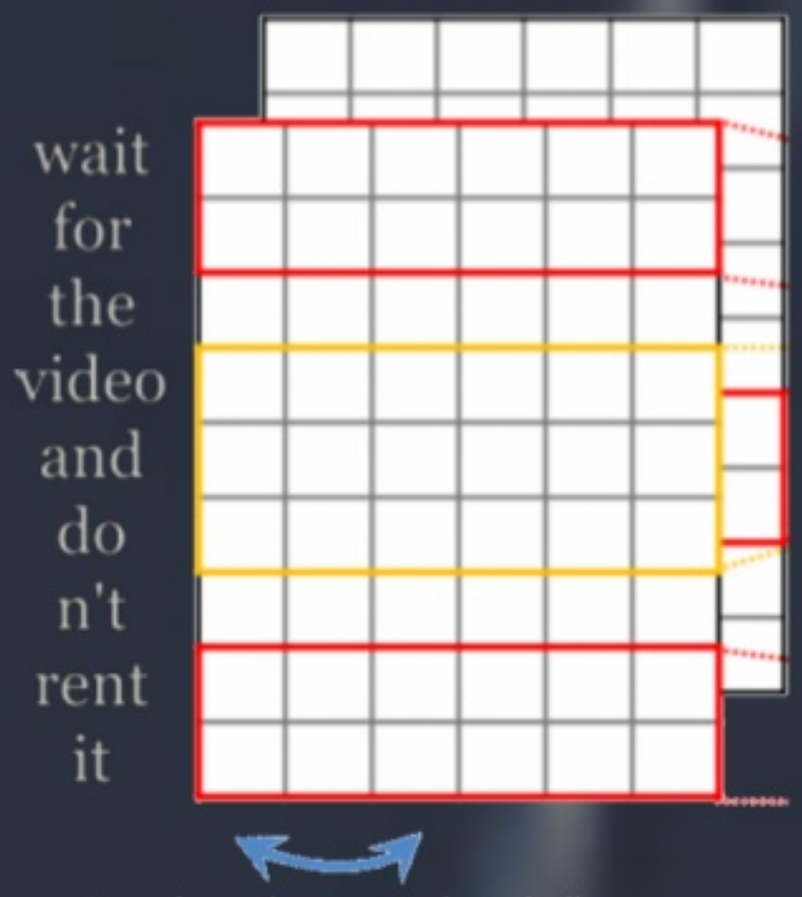


Bad idea #2: Semi-Supervised Learning of good/bad words

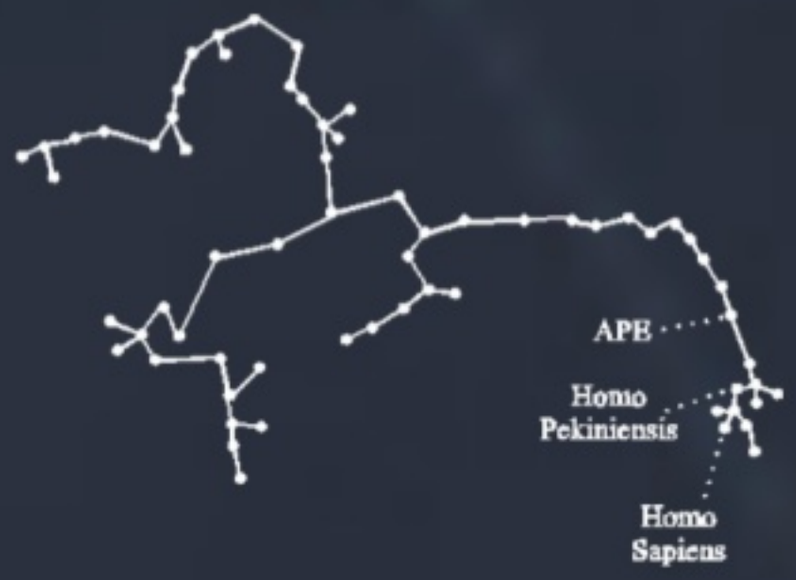
Bad idea #3: Co-occurrence graph to identify unigrams

- Really just bag of words

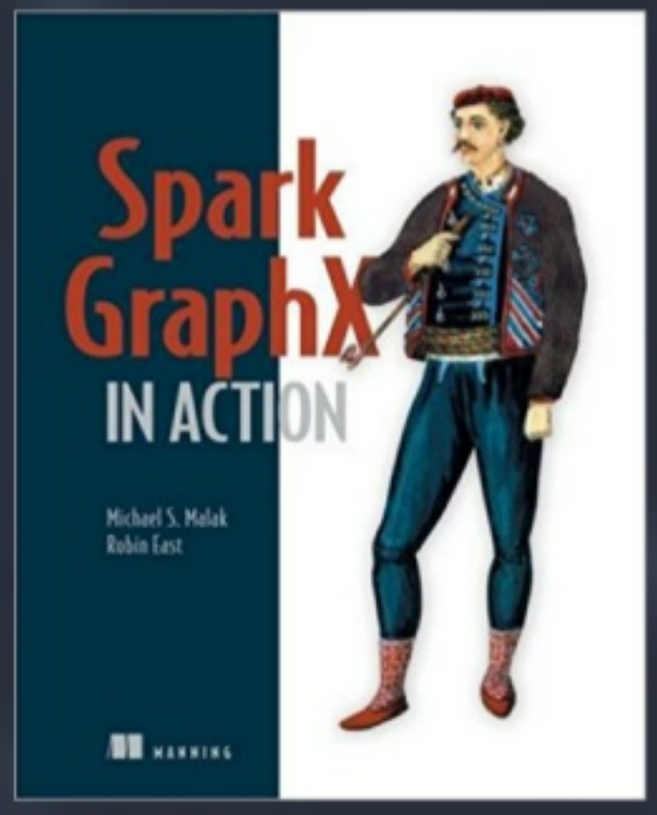
Bad idea #1: 2D CNN



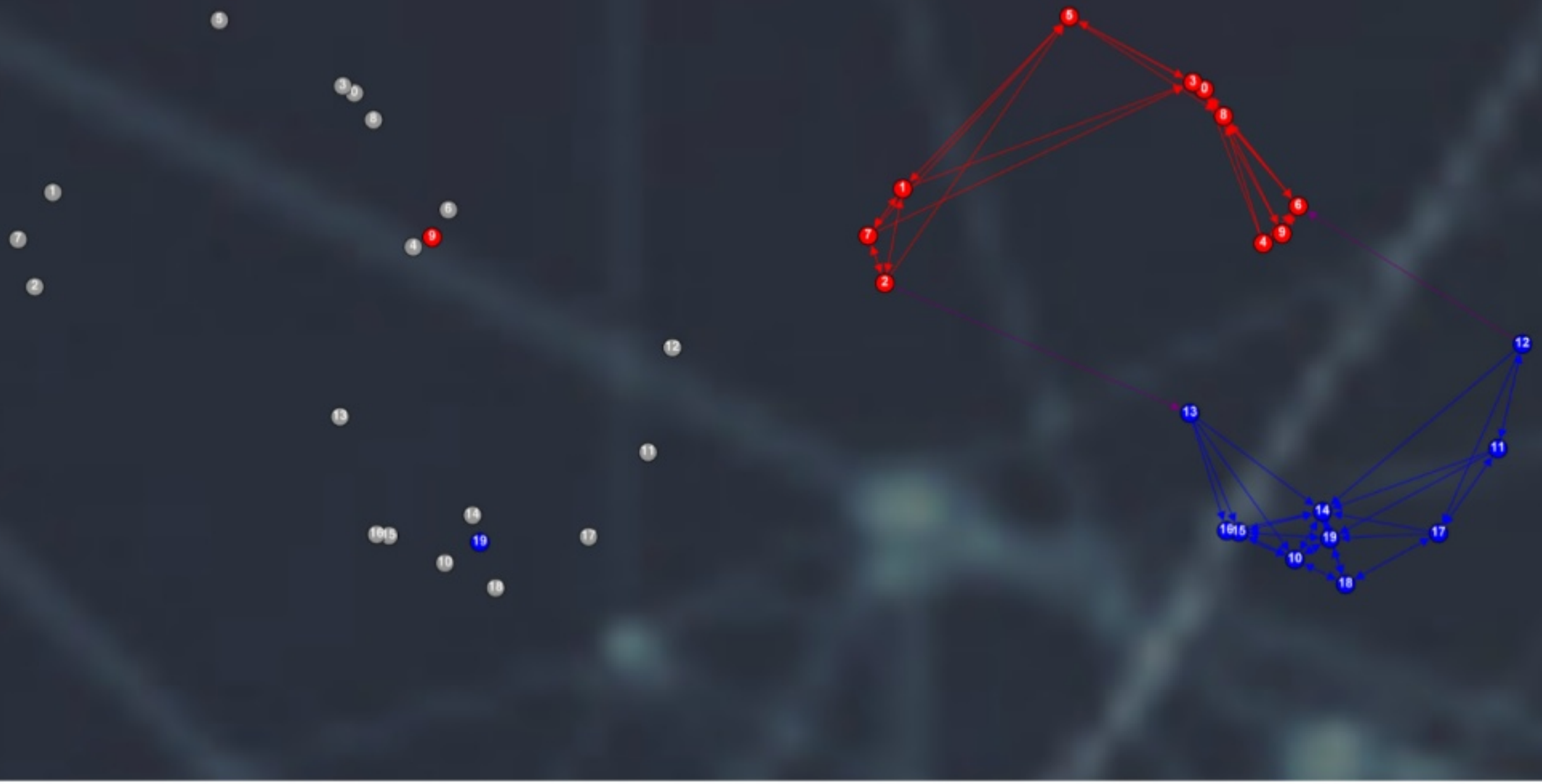
Reorder columns so that similar columns are near each other



Column order determined by minimum spanning tree of word2vec columns



Bad idea #2: Semi-Supervised Learning of good/bad words

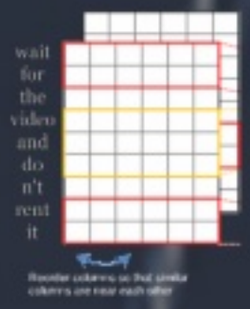


Bad idea #3: Co-occurrence graph to identify unigrams

- Really just bag of words

Dead Ends

Bad idea #1: 2D CNN



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Sentiment Analysis

Prior Techniques

Bag of Words

CNN & word2vec

CNN Plus Co-Occurrence Graphs

Idea

Implementation

Results

Dead Ends

Bad idea #1: 2D CNN

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Neuro-Symbolic Sentiment Analysis

SPARK SUMMIT 2017

Michael Malak

June 7, 2017

ORACLE Cloud

Big Data Preparation

Analytics Cloud

Summary

- Classic/symbolic AI and neuro-symbolic just now out of winter
- OK to say "AI" now
- Can improve over neural-only techniques
- Keras/Jupyter great prototyping tool
- DL4J great for word2vec and CNN under Spark (and GPU)
- Source code: technicaltidbit.com in 2-4 weeks

Neuro-Symbolic Sentiment Analysis

SPARK SUMMIT 2017

Michael Malak

June 7, 2017

ORACLE Cloud

Big Data Preparation

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