DEEP LEARNING & APPLICATIONS IN NON-COGNITIVE DOMAINS

PART II: PRACTICE

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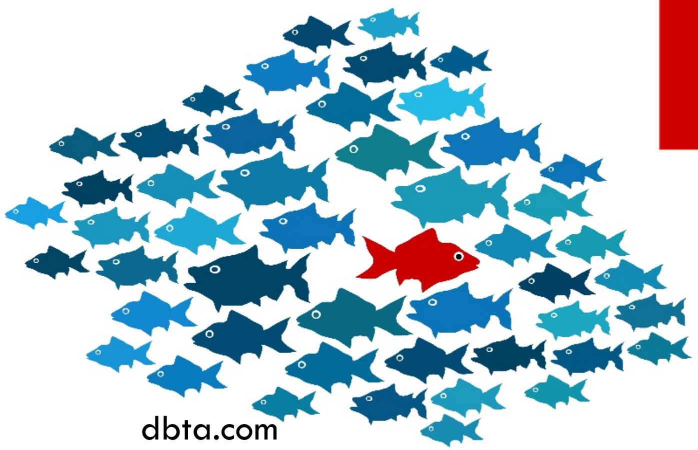
PART II: PRACTICE
APPLYING DEEP LEARNING TO NON-COGNITIVE DOMAINS

Hand-on:

- Introducing programming frameworks (Theano, TensorFlow, Mxnet)

Domains how-to:

- Healthcare
- Learning to rank objects
- Software engineering
- Anomaly detection
- Malicious URLs



COMPUTATIONAL GRAPHS

Everything is a **computational graph** from end-to-end.

Each block has an input and an output, and some tensor operators.

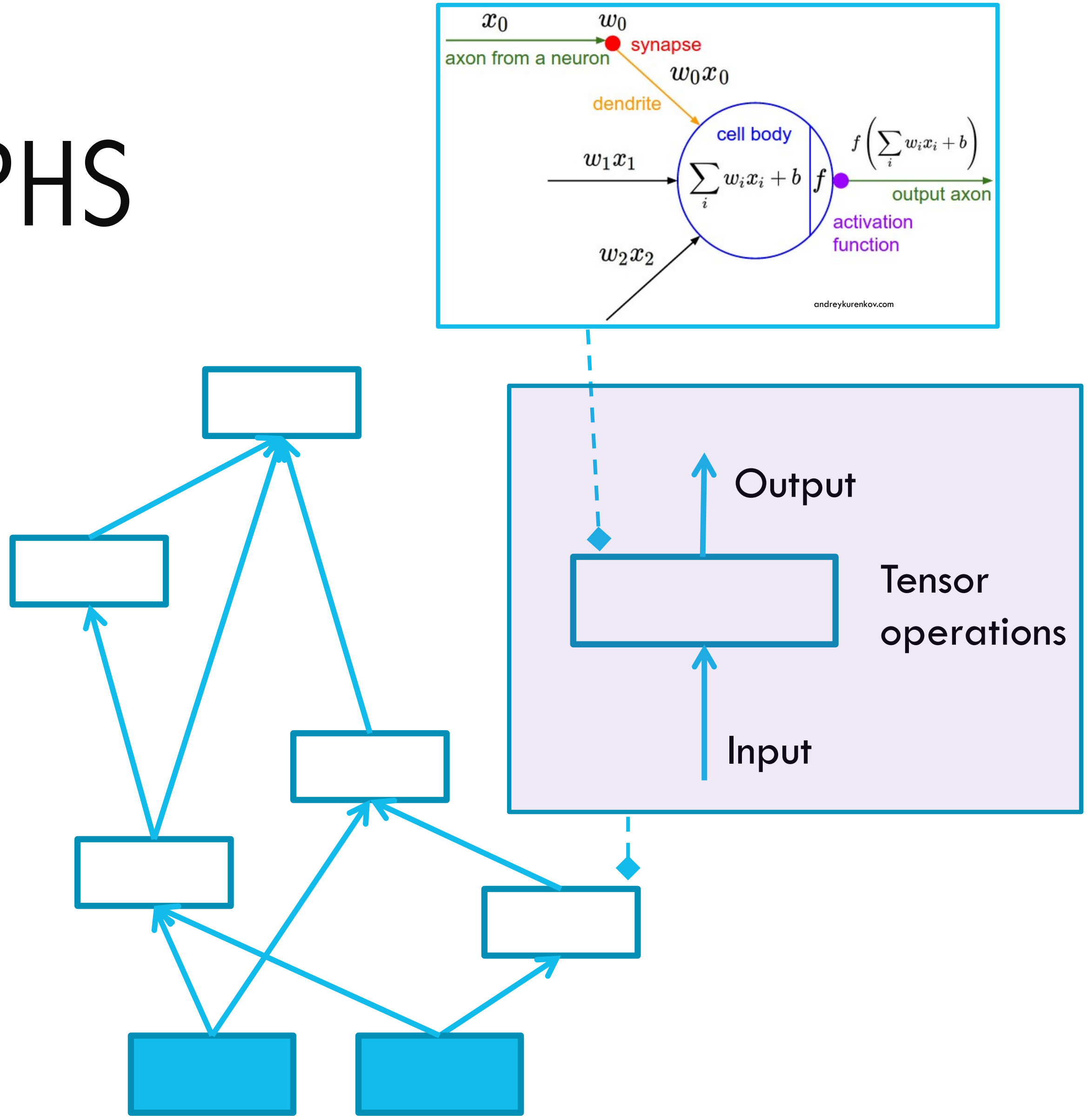
- Hence the name TensorFlow.

Vectors (1D), matrices (2D) and tensors N-D) operations

Element-wise transforms

Automatic differentiation naturally supported

… It is Lego building exercise!



CHOOSING THE RIGHT FRAMEWORK

Languages: **Python**, Matlab, Java, C/C++, R, Julia

Keys:

- **Automatic gradient**, if not, the needs checking from finite-difference methods.
- **GPU support**. Can be 10X-100X different.

Keras

Lasagne

Nolearn

TensorFlow (Google -- Python)

Theano (Montreal Uni -- Python)

Mxnet (collaborative work, supports C++, Python, Julia, Matlab, JavaScript, R, Scala)

Torch7 (Facebook, DeepMind, Twitter -- Lua)

Others: Caffe, CNTK, H2O, Chainer, etc.

THEANO & TENSORFLOW

Two most popular frameworks at present. Both in Python.

Theano

- Academic-driven. Pioneer.
- Symbolic computation → can be tricky to debug
- Wrapper: Lasagne, Keras

TensorFlow

- Google → Native distributed computing support
- A lot of support, huge community
- Slightly bigger/messier code
- Linux/Mac only but VirtualBox will help in Windows
- Wrapper: Keras

mxnet

- √ Excellent support for many languages
- √ Fast, portable
- √ Intuitive syntax
- √ Recent choice by AWS

Tensorflow vs. MXNET

	Languages	MultiGPU	Distributed	Mobile	Runtime Engine
Tensorflow	Python	**Yes**	No	**Yes**	?
MXNET	**Python, R, Julia, Go**	**Yes**	**Yes**	**Yes**	**Yes**

(Googlenet) E5-1650/980	Tensor flow	Torch7	Caffe	MXNET
Time	940ms	172ms	**170ms**	180ms
Memory	all (OOM after 24)	2.1GB	2.2GB	**1.6GB**

Marianas Labs — Carnegie Mellon University

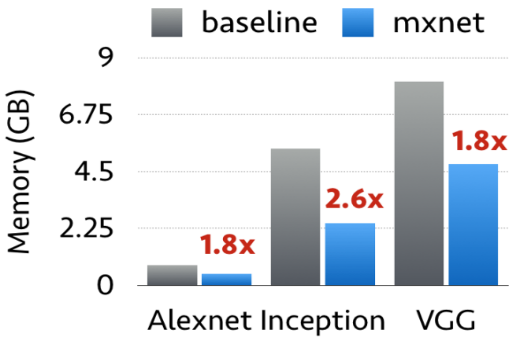
http://bickson.blogspot.com.au/2016/02/mxnet-vs-tensorflow.html

Portable

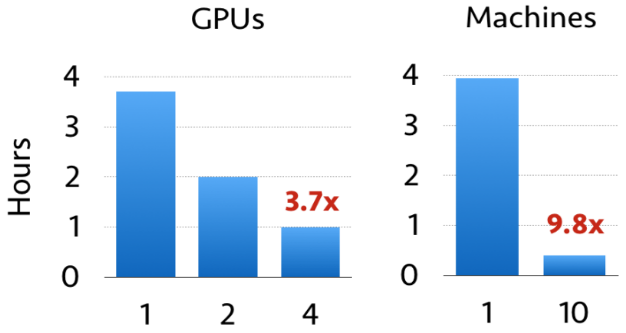
Scala JS julia Go

https://github.com/dmlc/mxnet

Efficient



Scalable



BUILDING A MODEL

Check the model assumption

- Is this only the vector → FNN?
- Is this a regular sequence → RNN?
- Is there repeated motifs → CNN?
- Is there a mix of static and dynamic features?
- What does the output look like?
  - A class
  - A sequence
  - An image?
- What are performance measures? → Surrogate smooth objective functions

Everything is a computational graph

From here to there is a tensor

So simple stacking is fine (the idea behind Keras)

Fit small datasets first to test the water

- But be cautious: small data do not always generalize

Always monitor the gap between train/validation sets: small gap indicates underfitting, big widening gap indicates overfitting.

STEPS

Prepare a clean big dataset

Design a suitable architecture → the main ART

Choose an optimizer (sgd, momentum, adagrad, adadelta, rmsprop, adam)

Normalise data (very important for fast training & well-behaved learning curve)

Shuffle data randomly (extremely important!)

Run the optimizer

Sit back & wait (in fact, should spend time monitor the convergence)

Grid search if time permits (sometimes very important to get correct convergence!)

Ensemble if time permits

Reiterate if needed

THINGS TO TAKE CARE OF

Data quality

Leakage

- Never touch validation data for feature engineering
- Be aware of overlapping between training/validation in time-sensitive data

Memory limitation

CPU/GPU time

Always shuffle the data <u>BEFORE</u> training – create a mixing of labels

Initialisation matters

Dropouts: almost always help, normally with bigger models. But be careful with RNNs.

Numerical overflow/underflow: exp of large number, log of or division by zeros

DETAILS

Learning algorithms

- Mostly adaptive SGD these days
- Much less using conjugate gradients & L-BFGS due to non-convexity
- Things to worry about: learning rate, mini-batch size, length normalization

For sequences

- Max sequence length (for fast implementation)
- For discrete domains such as NLP, then vocab size, otherwise, use NCE approximation.

For motifs

- Filter size, stride, number of filters, pooling methods

Dropouts

- Hidden is easy: 50% works pretty well
- Input is trickier: larger (up to 20%) for noisy & redundant data

Convergence monitoring

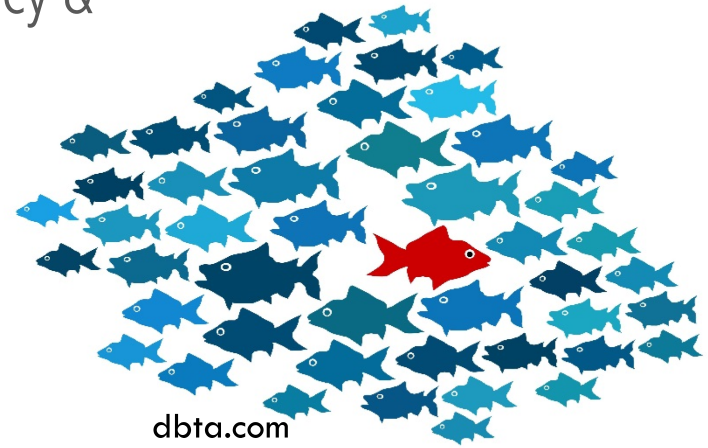
- Always do
- Check overfitting & underfitting

APPLYING TO NON-COGNITIVE DOMAINS

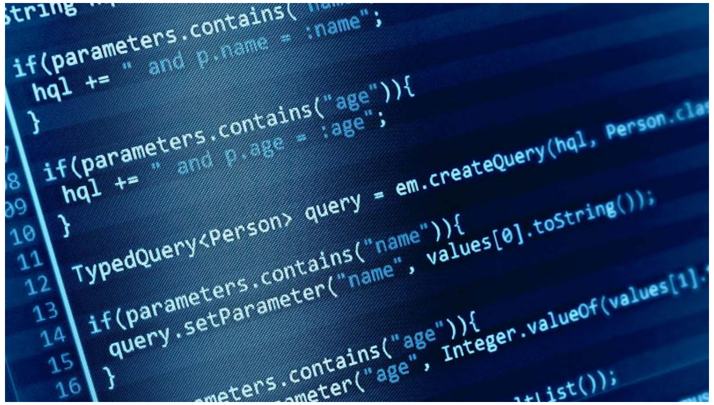
freewebmentor.com

- Where humans need extensive training to do well
- Domains with great diversity but may be small in size
- Domains with great uncertainty, low-quality/missing data
- Domains that demand transparency & interpretability.

Healthcare
Software engineering
Information retrieval
Anomaly detection



dbta.com



http://www.bentoaktechnologies.com/Images/code_scrn.jpg

WHAT MAKE NON-COGNITIVE DOMAINS HARD?

Reusable models do not usually exist

Require deep thinking for a reasonable deep architecture

However, at the end of the day, we need few generic things:

- Vector -> DNN (e.g., highway net)
- Sequence -> RNN (e.g., LSTM, GRU)
- Repeated Motifs -> CNN
- Set -> attention (Will visit in Part III)
- Graphs -> Column Networks (Will visit in Part III)

Epworth HealthCare

Barwon Health

THE UNIVERSITY OF SYDNEY

DEAKIN UNIVERSITY AUSTRALIA Worldly

HEALTHCARE

HEALTHCARE: CHALLENGES + OPPORTUNITIES

Long-term dependencies

Irregular timing

Mixture of discrete codes and continuous measures

Complex interaction of diseases and care processes

Cohort of interest can be small (e.g., <1K)

May include textual notes

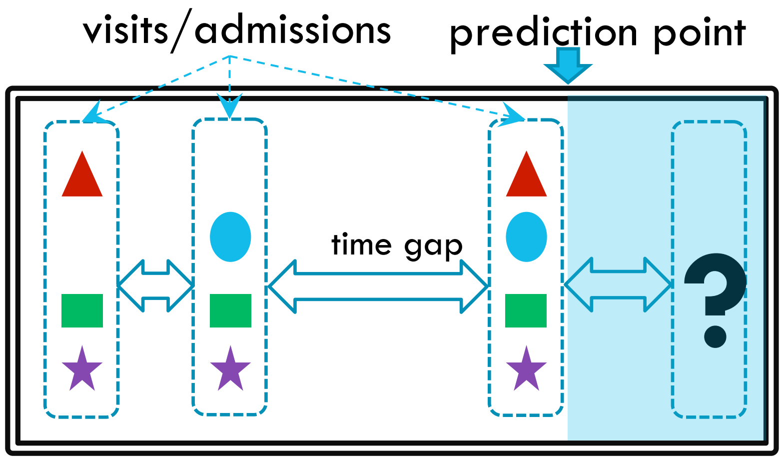
May contain signals (e.g., EEG/ECG)

May contain images (e.g., MRI, X-ray, retina)

Rich domain knowledge & ontologies

THIS TUTORIAL WILL COVER:

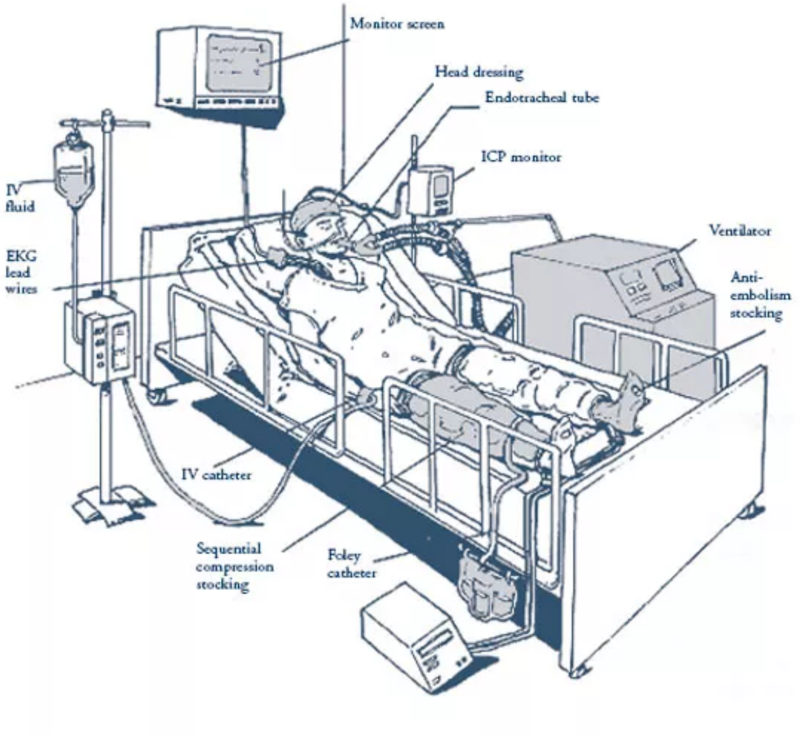
Electronic medical records (EMR)



- Time-stamped
- Coded data: diagnosis, procedure & medication
- Text not considered, but in principle can be mapped in to vector using LSTM

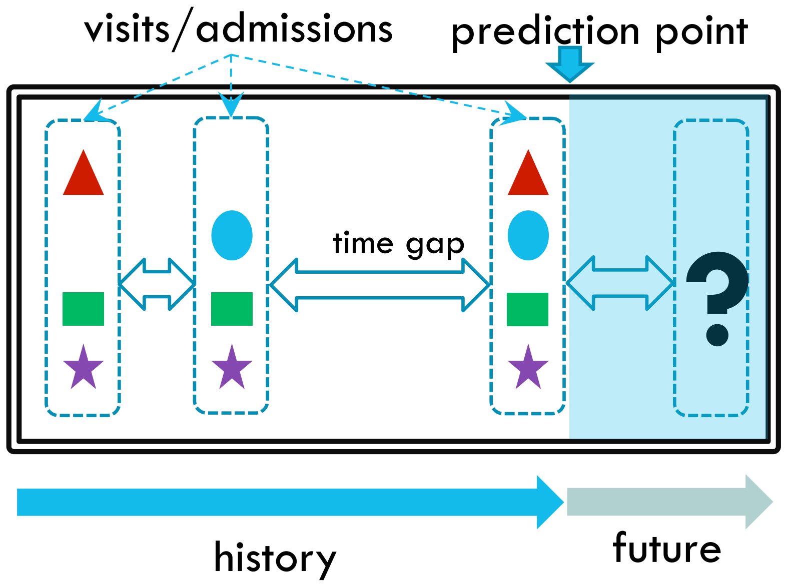
Physiological measures in Intensive Care Unit (CU)

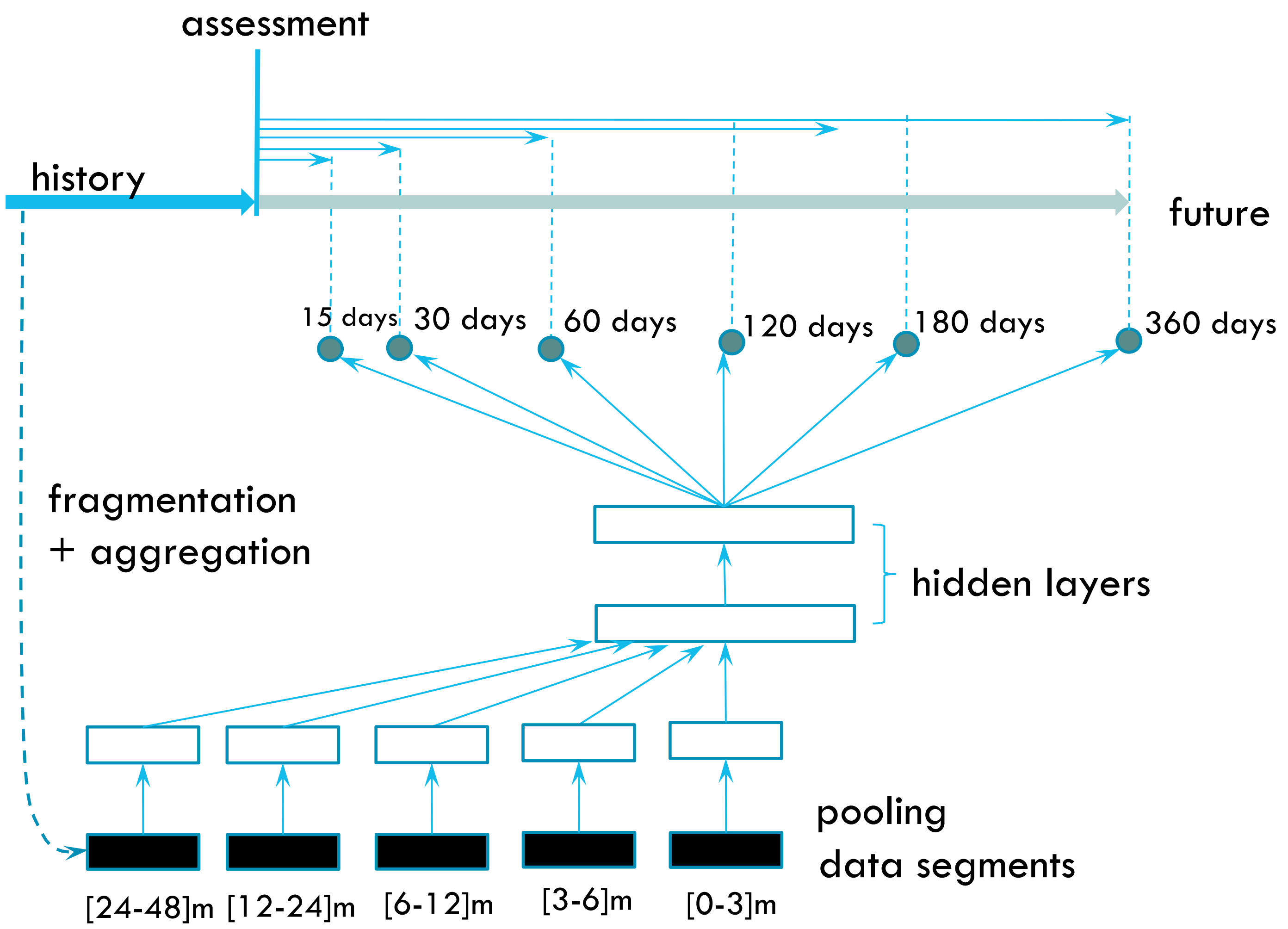
<Time, Type, Value>



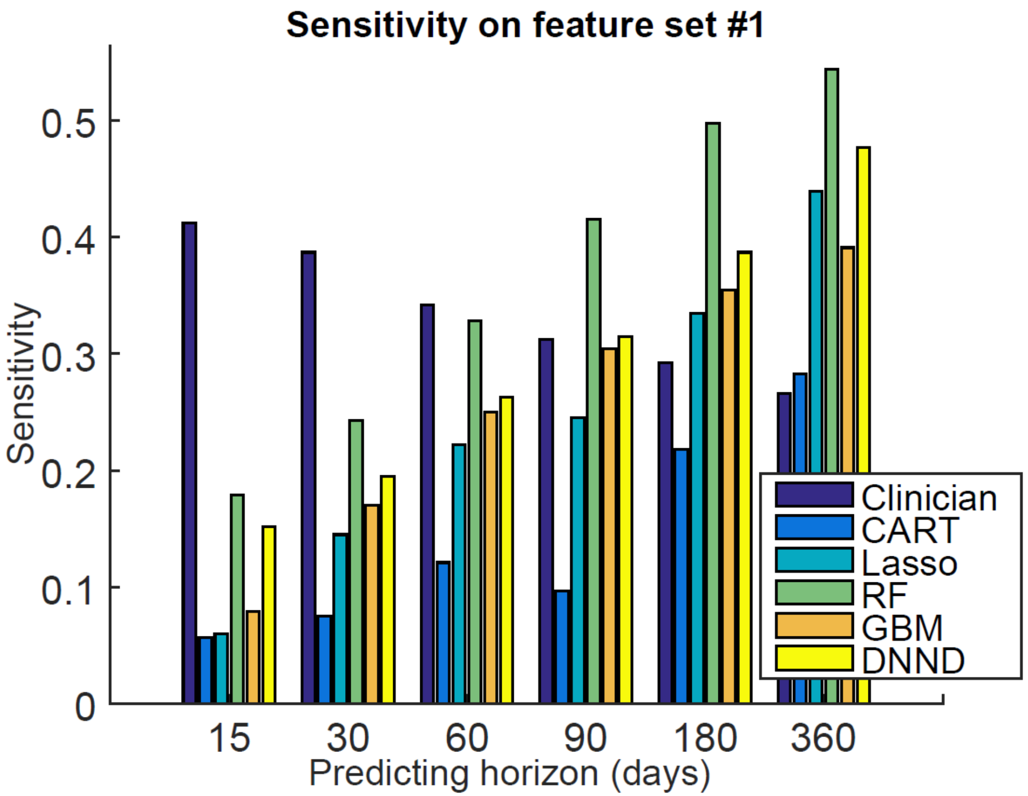
http://www.healthpages.org/brain-injury/brain-injury-intensive-care-unit-icu/

MEDICAL RECORDS: FEEDFORWARD NETS

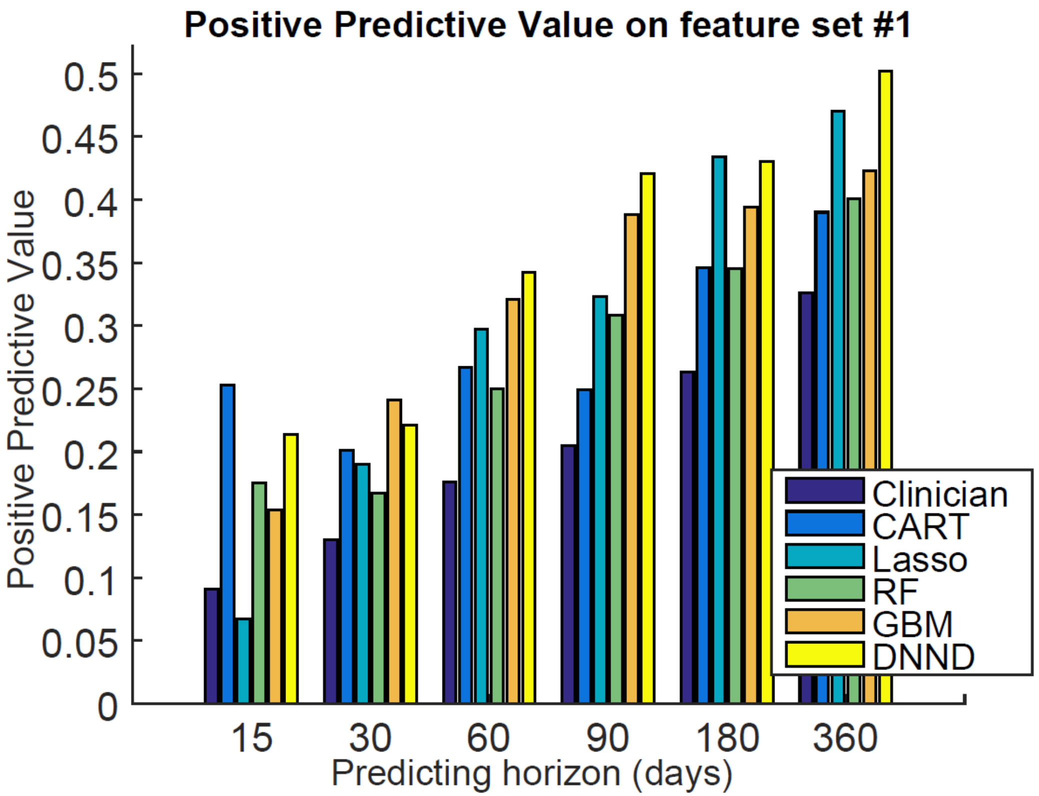




SUICIDE RISK PREDICTION: MACHINE VERSUS CLINICIAN

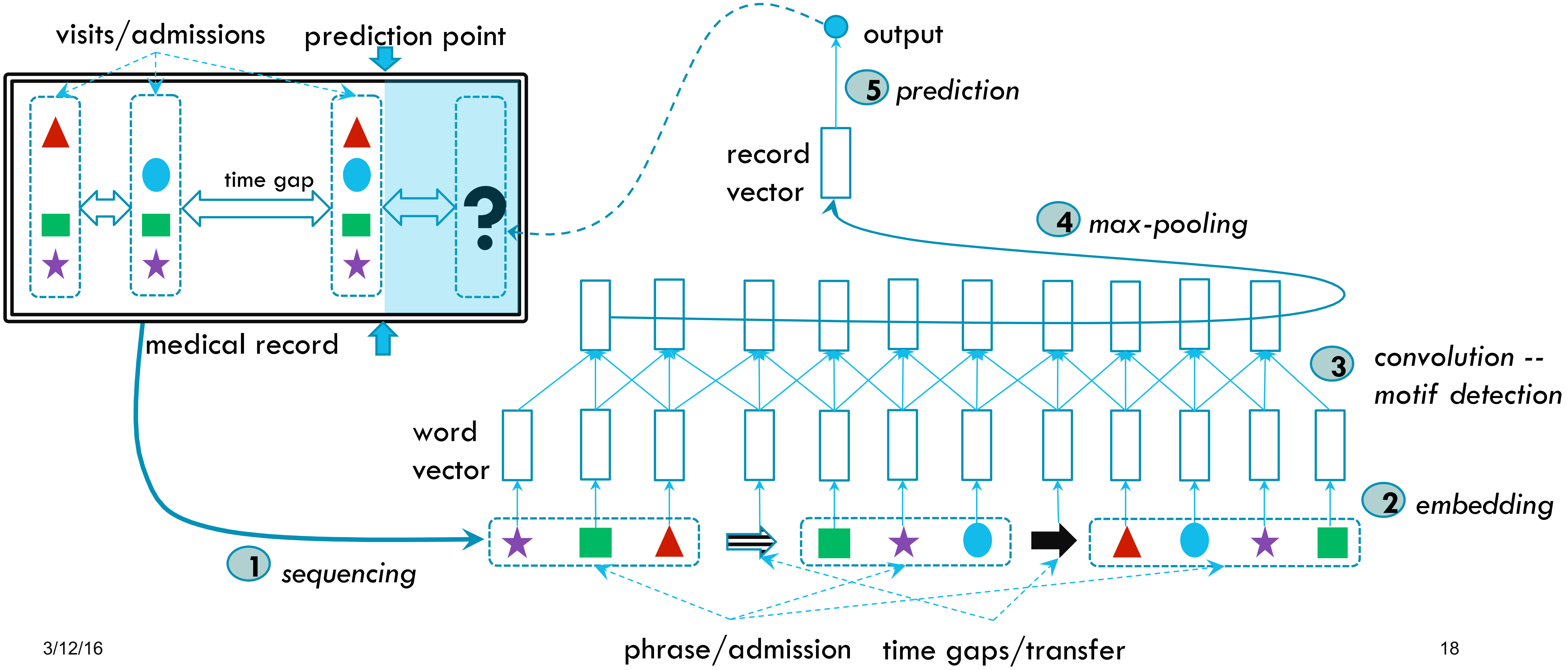


(a) Recall



(b) Precision

DEEPR: CNN FOR REPEATED MOTIFS AND SHORT SEQUENCES (NGUYEN ET AL, J-BHI, 2016)



DISEASE EMBEDDING & MOTIFS DETECTION

E11 I48 I50

Type 2 diabetes mellitus

Atrial fibrillation and flutter

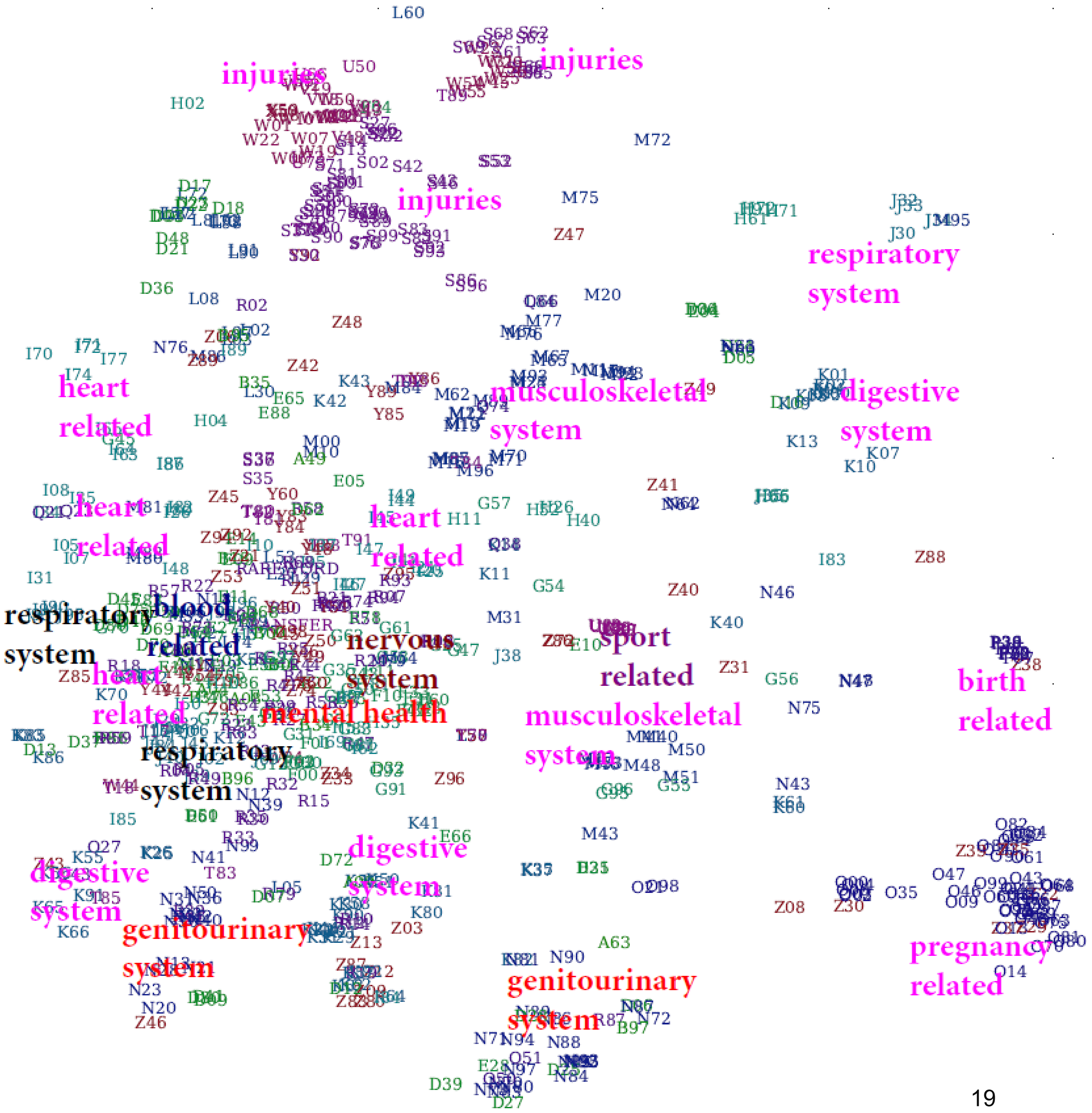
Heart failure

E11 I50 N17

Type 2 diabetes mellitus

Heart failure

Acute kidney failure



DEEPCARE FOR INTERVENED LONG-TERM MEMORY OF HEALTH (PHAM ET AL, ICPR'16)

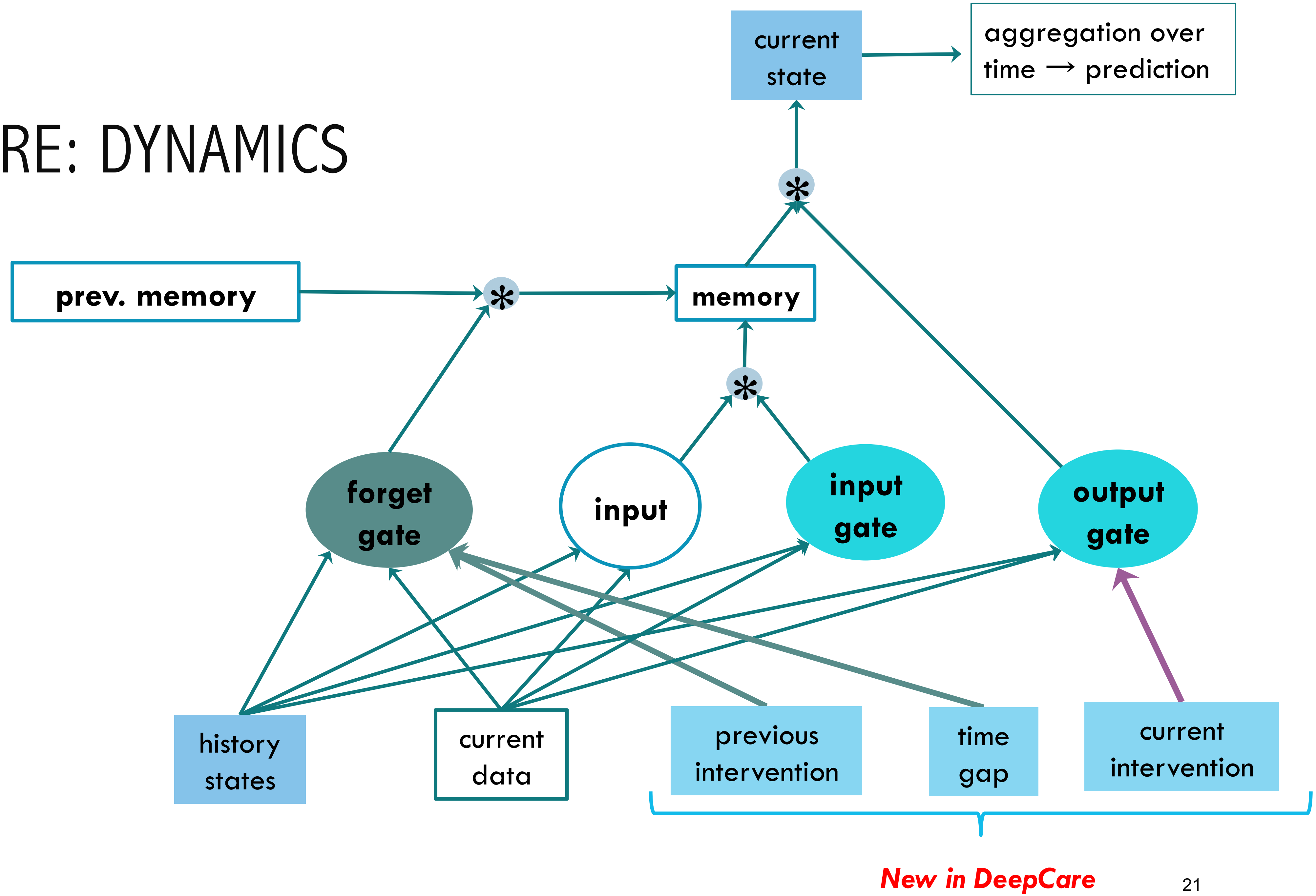
Illness states are a dynamic memory process → moderated by time and intervention

Discrete admission, diagnosis and procedure → vector embedding

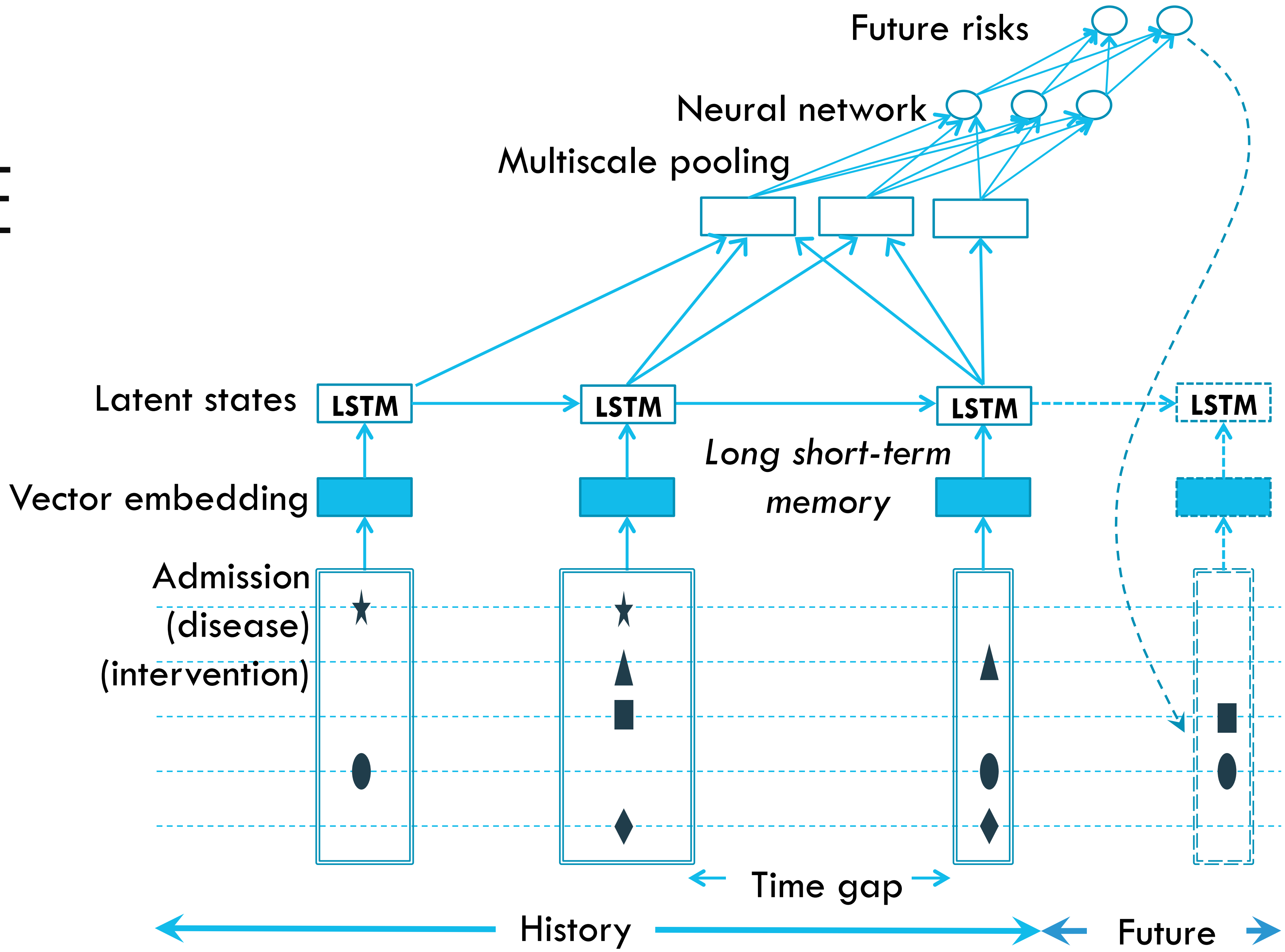
Time and previous intervention → "forgetting" of illness

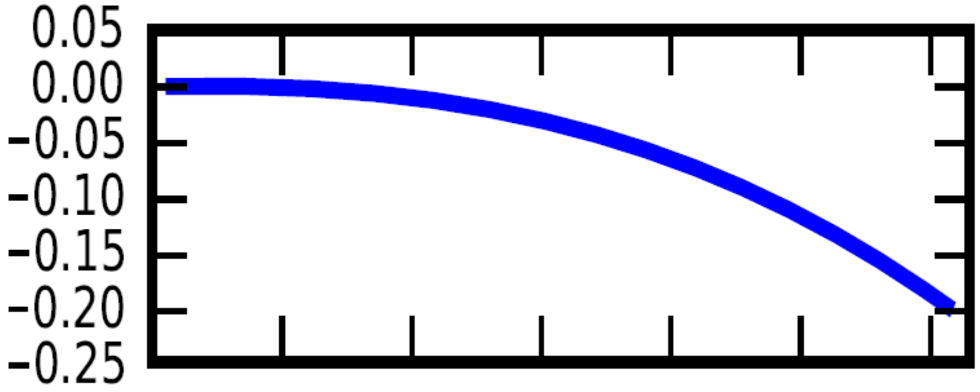
Current intervention → controlling the risk states

DEEPCARE: DYNAMICS

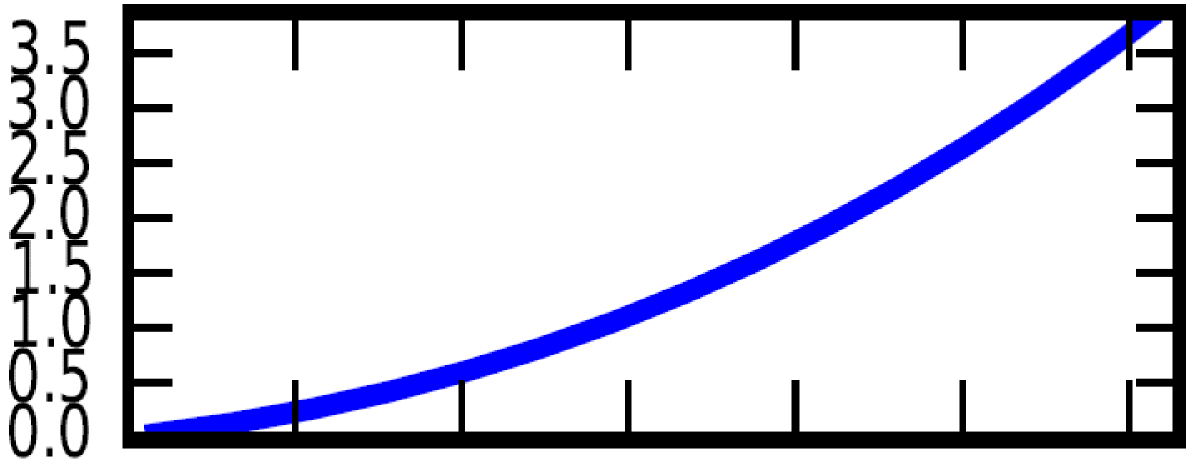


DEEPCARE: STRUCTURE





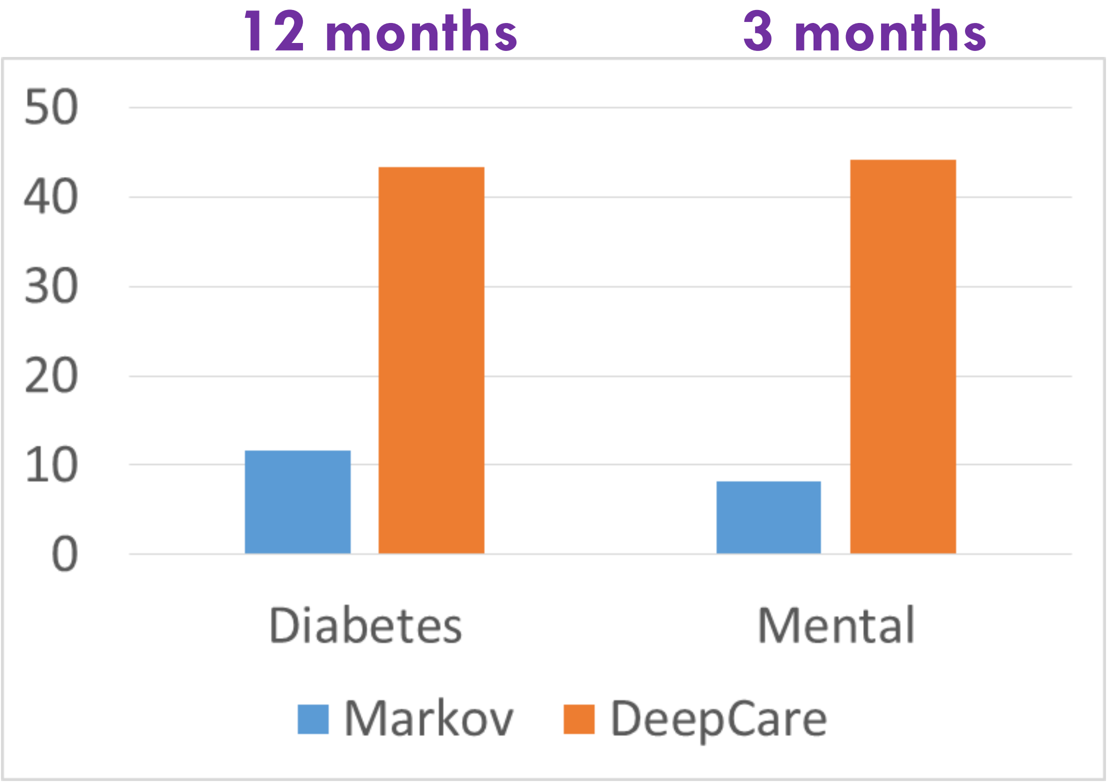
→ decreasing illness

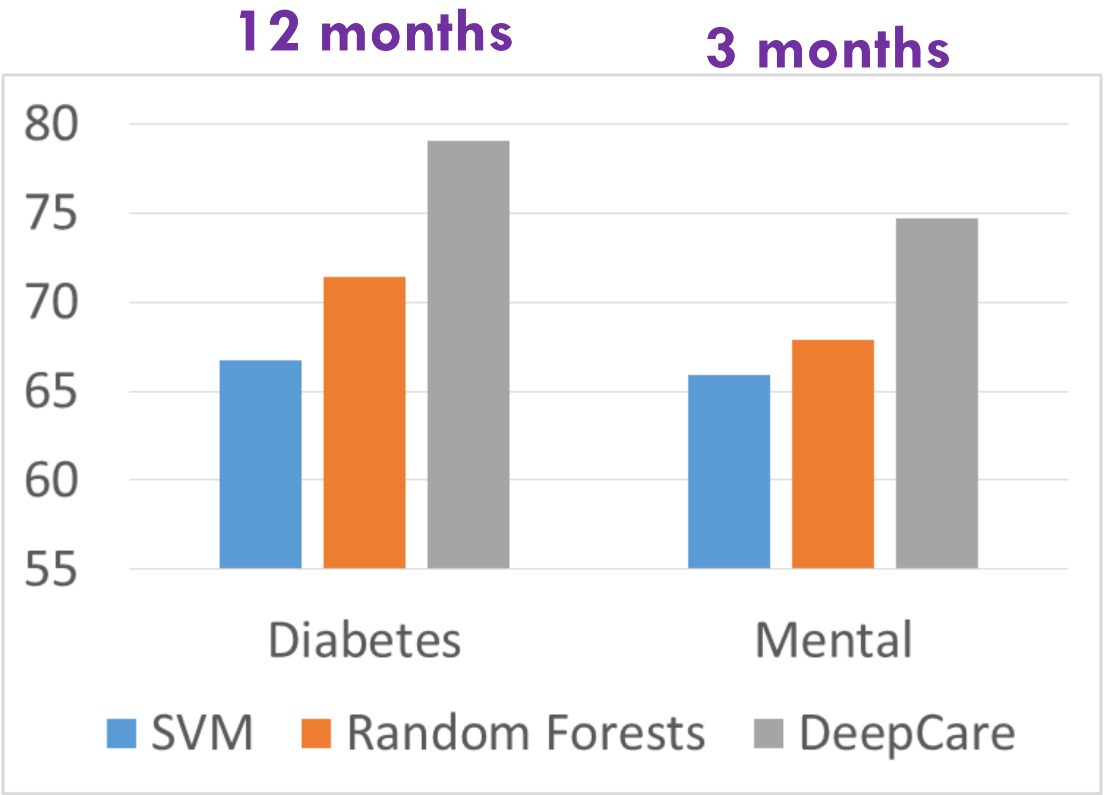


→ Increasing illness

DEEPCARE: TWO MODES OF FORGETTING AS A FUNCTION OF TIME

DEEPCARE: PREDICTION RESULTS





Intervention recommendation (precision@3)

Unplanned readmission prediction (F-score)

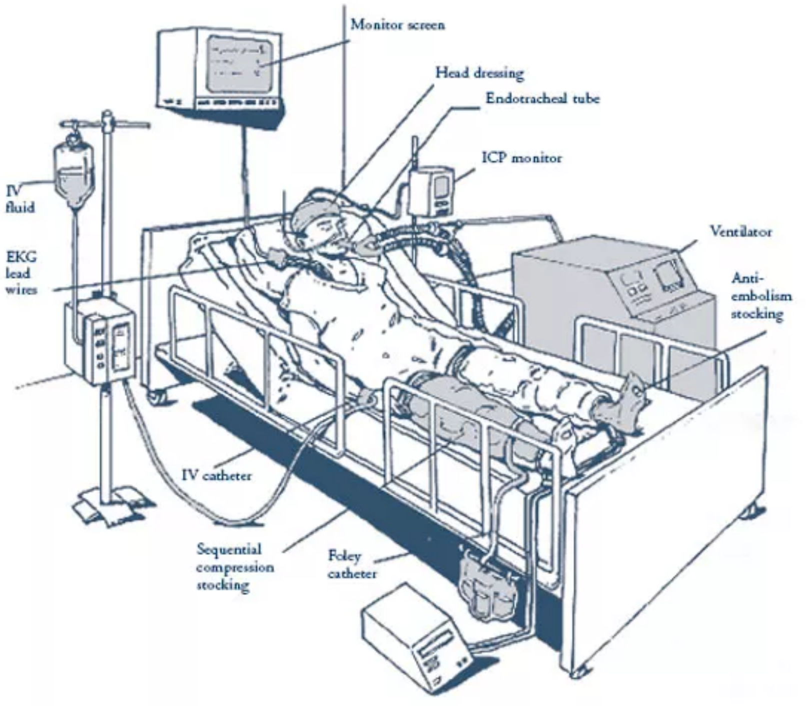
DEEPIC: MORTALITY PREDICTION IN INTENSIVE CARE UNITS (WORK IN PROGRESS)

Existing methods: LSTM with missingness and time-gap as input.

New method**: Deepic**

Steps:

- Measurement quantization
- Time gap quantization
- Sequencing words into sentence
- CNN

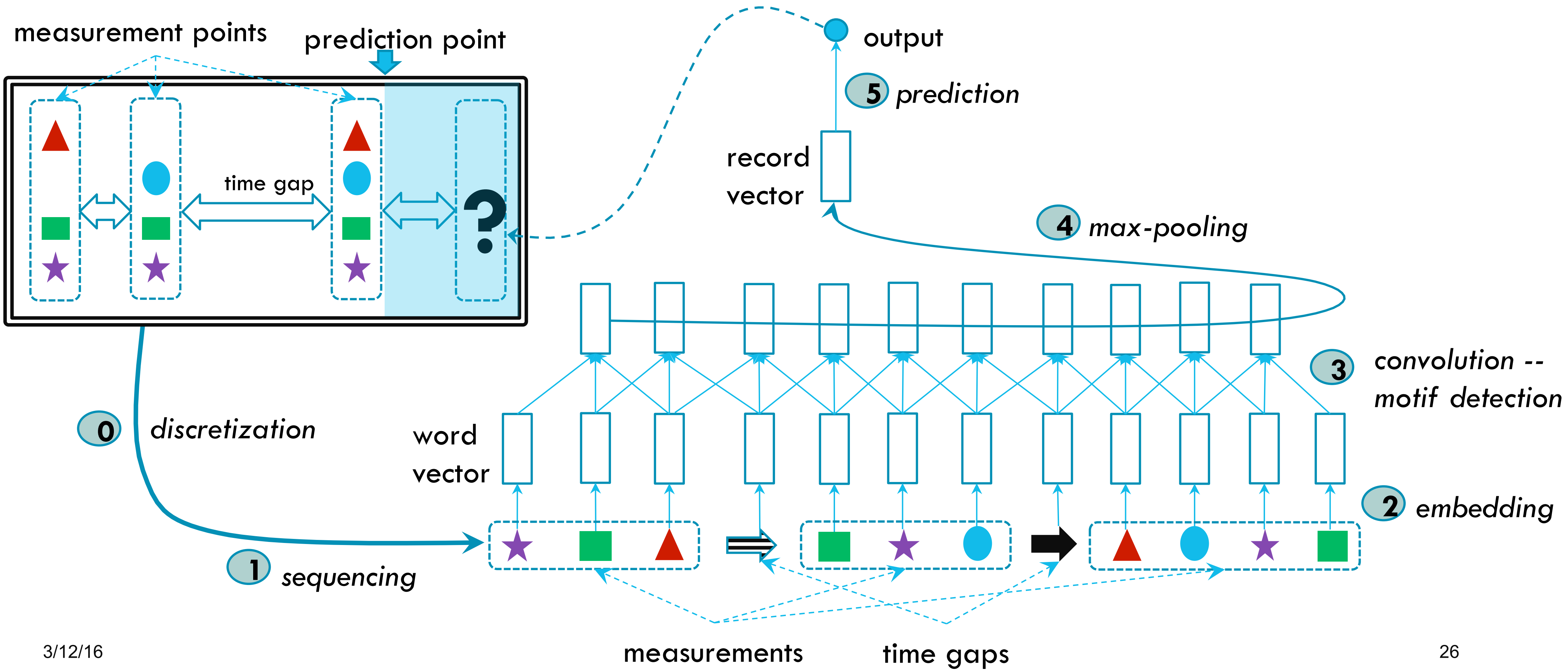


http://www.healthpages.org/brain-injury/brain-injury-intensive-care-unit-icu/

Time,Parameter,Value
00:00,RecordID,132539
00:00,Age,54
00:00,Gender,0
00:00,Height,-1
00:00,ICUType,4
00:00,Weight,-1
00:07,GCS,15
00:07,HR,73
00:07,NIDiasABP,65
00:07,NIMAP,92.33
00:07,NISysABP,147
00:07,RespRate,19
00:07,Temp,35.1
00:07,Urine,900
00:37,HR,77
00:37,NIDiasABP,58
00:37,NIMAP,91
00:37,NISysABP,157
00:37,RespRate,19
00:37,Temp,35.6
00:37,Urine,60

Data: **Physionet 2012**

DEEPIC: **SYMBOLIC** & TIME GAP REPRESENTATION OF DATA



SOFTWARE ANALYTICS

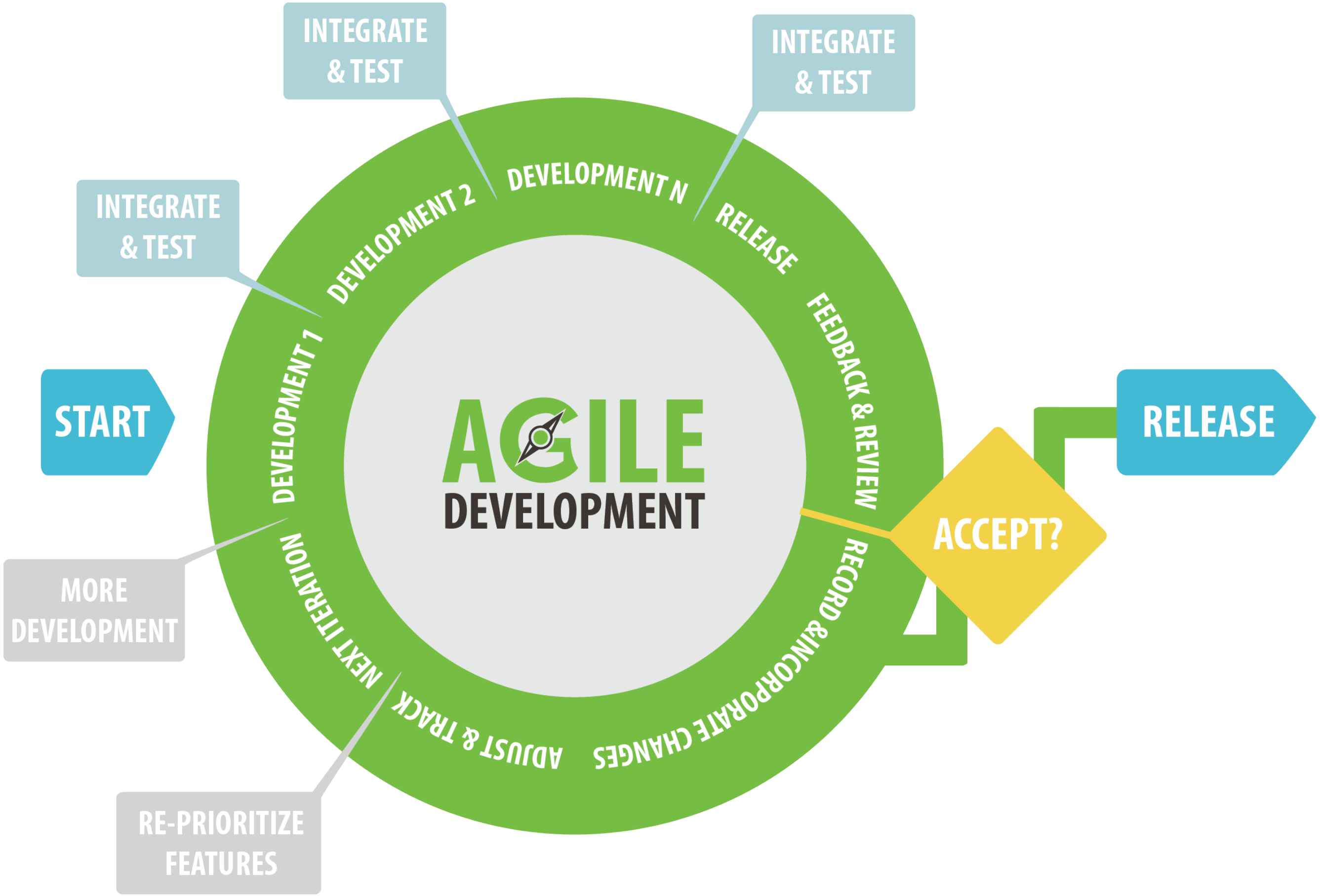
DATA-DRIVEN SOFTWARE ENGINEERING





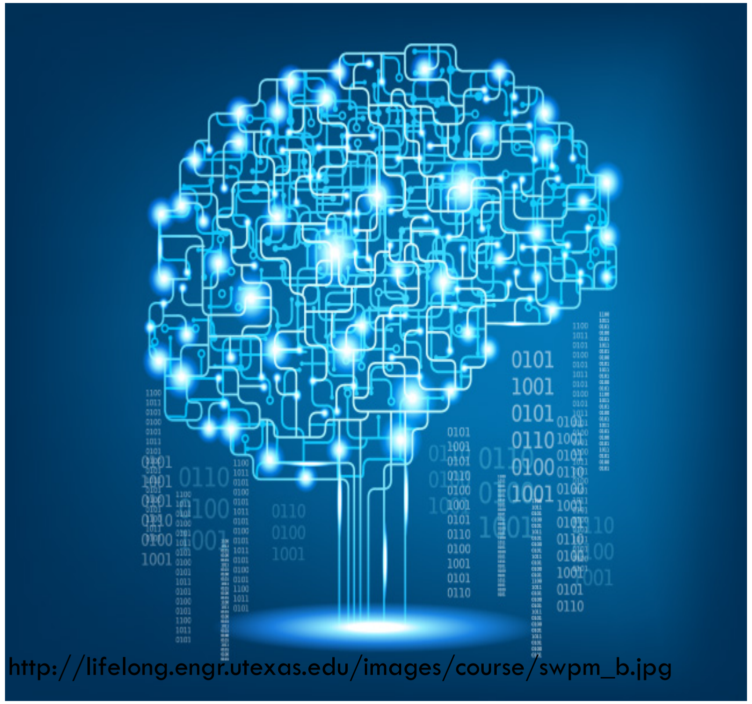
http://www.bentoaktechnologies.com/Images/code_scrn.jpg

ANALYTICS FOR AGILE SOFTWARE PROJECT MANAGEMENT



http://www.solutionguidance.com/?page_id=1579

TOWARDS INTELLIGENT ASSISTANTS



http://lifelong.engr.utexas.edu/images/course/swpm_b.jpg

Goal: To model code, text, team, user, execution, project & enabled business process → answer any queries by developers, managers, users and business

- End-to-end
- Compositional

For now:

- DeepSoft vision
- LSTM for code language model
- LD-RNN for report representation
- Stacked/deep inference (later)

CHALLENGES: LONG-TERM TEMPORAL DEPENDENCIES IN SOFTWARE

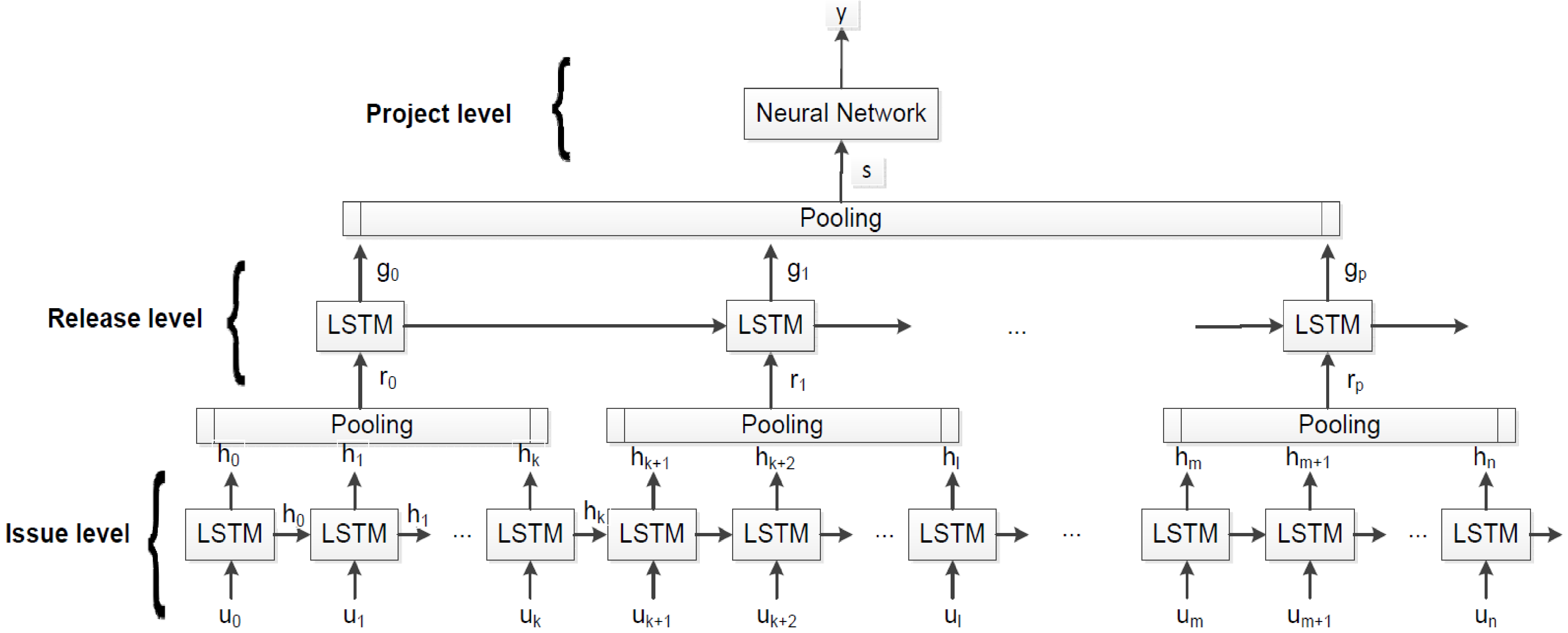
Software is similar to an **evolving** organism

- What will happen next to a software system depends heavily on what has previously been done to it.
- E.g. the implementation of a functionality may constraint how other functionalities are implemented in the *future*.
- E.g. a *previous* change (to fix a bug or add a new feature) may inject *new* bugs and lead to further changes.
- E.g. refactoring a piece of code may have *long-term* benefits in *future* maintenance.

Today's software products undergo rapid cycles of development, testing and release

- A software **project** typically has many **releases**
- A release requires the completion of some tasks (i.e. resolution of some **issues**).
- An issue is described using natural language (*raw data*).
- The resolution of an issue may result in code patches (*raw data*).

DEEPSOFT: COMPOSITIONAL DEEP NET FOR SW PROJECT (DAM ET AL, FSE'16)



A DEEP LANGUAGE MODEL FOR SOFTWARE CODE (DAM ET AL, FSE'16 SE+NL)

A good language model for source code would capture the long-term dependencies

The model can be used for various prediction tasks, e.g. defect prediction, code duplication, bug localization, etc.

The model can be extended to model software and its development process.

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CHARACTERISTICS OF SOFTWARE CODE

Repetitiveness

- E.g. for (int i = 0; i < n; i++)

Localness

- E.g. *for (int size* may appear more often that *for (int i* in some source files.

Rich and explicit structural information

- E.g. nested loops, inheritance hierarchies

Long-term dependencies

- *try* and *catch* (in Java) or file *open* and *close* are not immediately followed each other.

A LANGUAGE MODEL FOR SOFTWARE CODE

Given a code sequence s= <w_1, …, w_k>, a language model estimate the probability distribution P(s):

$$P(s) = P(w_1) \prod_{t=2}^{k} P\left(w_t \mid \boldsymbol{w}_{1:t-1}\right)$$

where $\boldsymbol{w}_{1:t-1} = (w_1, w_2, ..., w_{t-1})$ is the historical *context* used to estimate the probability of the next code token w_t.

N-GRAMS MODEL

Truncates the history length to n-1 words (usually 2 to 5 in practice)

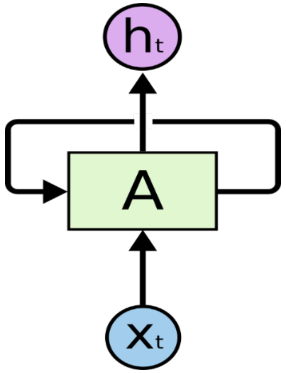
Useful and intuitive in making use of repetitive sequential patterns in code

Context limited to a few code elements

- Not sufficient in complex SE prediction tasks.

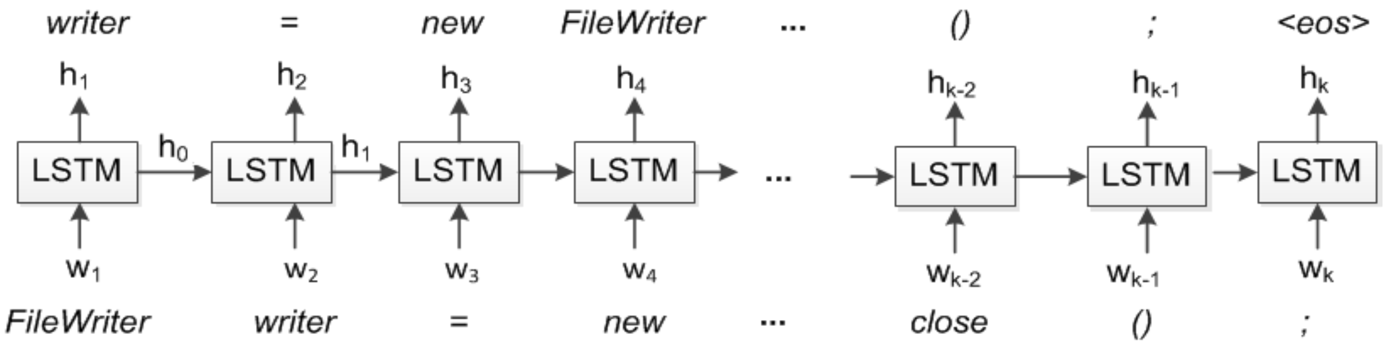
As we read a piece of code, we understand each code token based on our understanding of previous code tokens, i.e. the information persists.

CODE LANGUAGE MODEL




```
FileWriter writer = new FileWriter(file);
writer.write(``This is an example'');
int count = 0;
System.out.prinltln(``Long gap'');
    ......

writer.flush();
writer.close();
```



Previous work has applied RNNs to model software code *(White et al, MSR 2015)*

RNNs however do not capture the long-term dependencies in code

EXPERIMENTS

Built dataset of 10 Java projects: Ant, Batik, Cassandra, Eclipse-E4, Log4J, Lucene, Maven2, Maven3, Xalan-J, and Xerces.

Comments and blank lines removed. Each source code file is tokenized to produce a sequence of code tokens.

- Integers, real numbers, exponential notation, hexadecimal numbers replaced with <num> token, and constant strings replaced with <str> token.
- Replaced less “popular” tokens with <unk>

Code corpus of 6,103,191 code tokens, with a vocabulary of 81,213 unique tokens.

EXPERIMENTS (CONT.)

Datasets: training, validation/development, test

The size of the memory cell (c_t) is the same as the embedding dimension.

RMSprop used for tuning.

Two experimental settings:

- *Varied the maximum sequence length from 10 to 500 tokens*
- *Varied the embedding dimensionality from 20 to 500*

EXPERIMENTS (CONT.)

sent-len	embed-dim	RNN	LSTM	improv %
10	50	13.49	12.86	**4.7**
20		10.38	9.66	**6.9**
50		7.93	6.81	**14.1**
100		7.20	6.40	**11.1**
200		6.64	5.60	**15.7**
500		6.48	4.72	**27.2**
100	20	7.96	7.11	**10.7**
	50	7.20	6.40	**11.1**
	100	7.23	5.72	**20.9**
	200	9.14	5.68	**37.9**

Table 1: Perplexity on test data (the smaller the better).

Both RNN and LSTM improve with more training data (whose size grows with sequence length).

LSTM consistently performs better than RNN: 4.7% improvement to 27.2% (varying sequence length), 10.7% to 37.9% (varying embedding size).

STORY POINT ESTIMATION

Traditional estimation methods require experts, LOC or function points.

- Not applicable early
- Expensive

Feature engineering is not easy!

Needs a cheap way to start from just a documentation.

Spring XD / XD-2970

Standardize XD logging to align with Spring Boot Title

Type:	Story	Status:	DONE
Priority:	Major	Resolution:	Complete
Affects Version/s:	1.2 GA	Fix Version/s:	1.2 RC1
Story Points:	8		
Sprint:	Sprint 49		

Description

In XD today we use commons-logging or slf4j APIs bound to log4j at runtime (configured with log4j.properties).

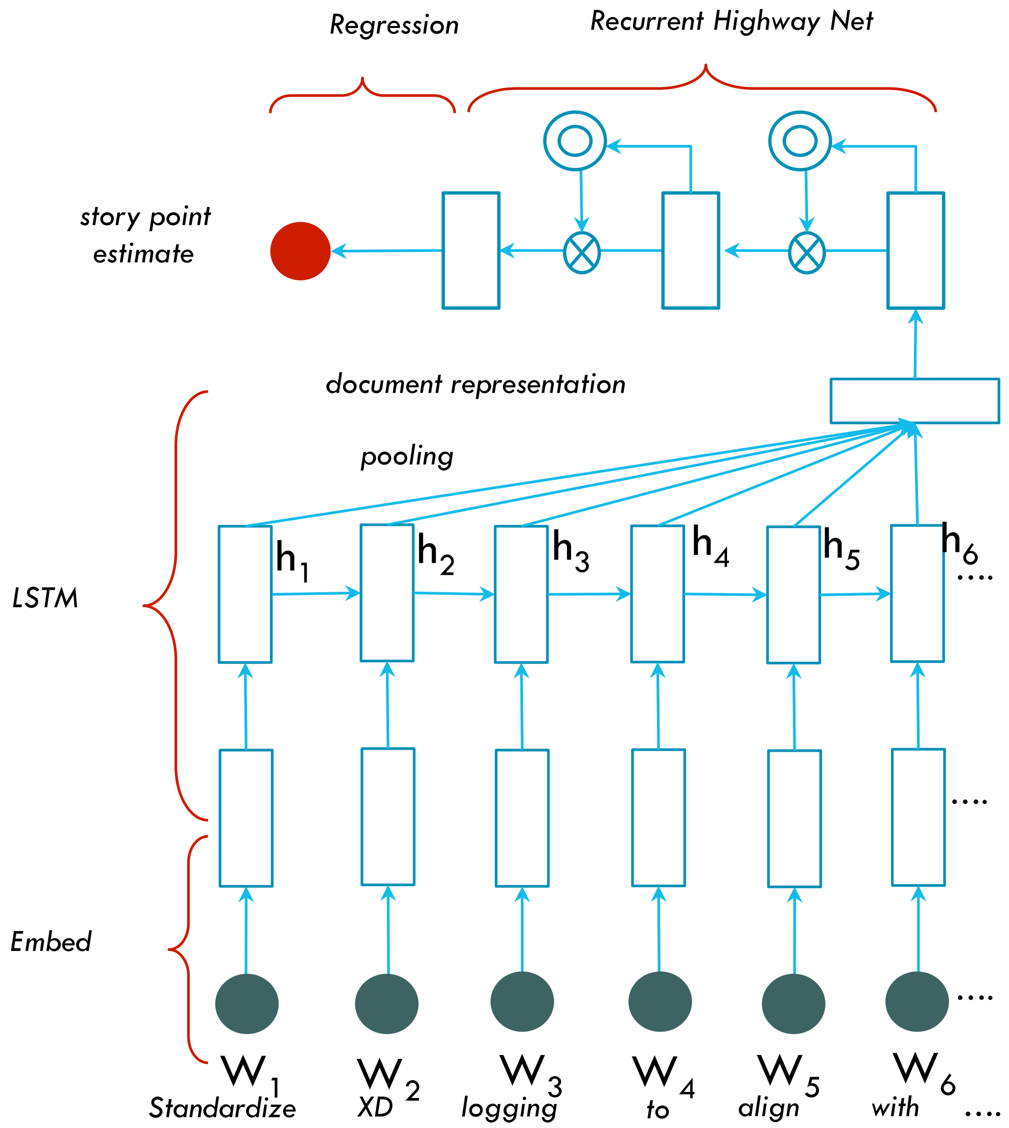
Boot uses slf4j APIs backed by logback. This causes some build incompatibilities building a component that depends on spring-xd-dirt and spring-boot, requiring specific dependency exclusions. In order to simplify building and troubleshooting log dependencies, XD should standardize on
slf4j APIs (replace any commons-logging Loggers with Slf4j). This is internal only, and would not impact users who are used to seeing log4j.properties. An additional step is to replace log4j with logback. This change would be visible to end users but will provide us greater affinity with boot and improve the developer experience. If we make this change it should go into 1.2 GA.

LD-RNN FOR REPORT REPRESENTATION
(CHOETKIERTIKUL ET AL, WORK IN PROGRESS)

LD = Long Deep

LSTM for document representation

Highway-net with tied parameters for story point estimation



RESULTS

MAE = Mean Absolute Error

$$SA = \left(1 - \frac{MAE}{MAE_{rguess}}\right) \times 100$$

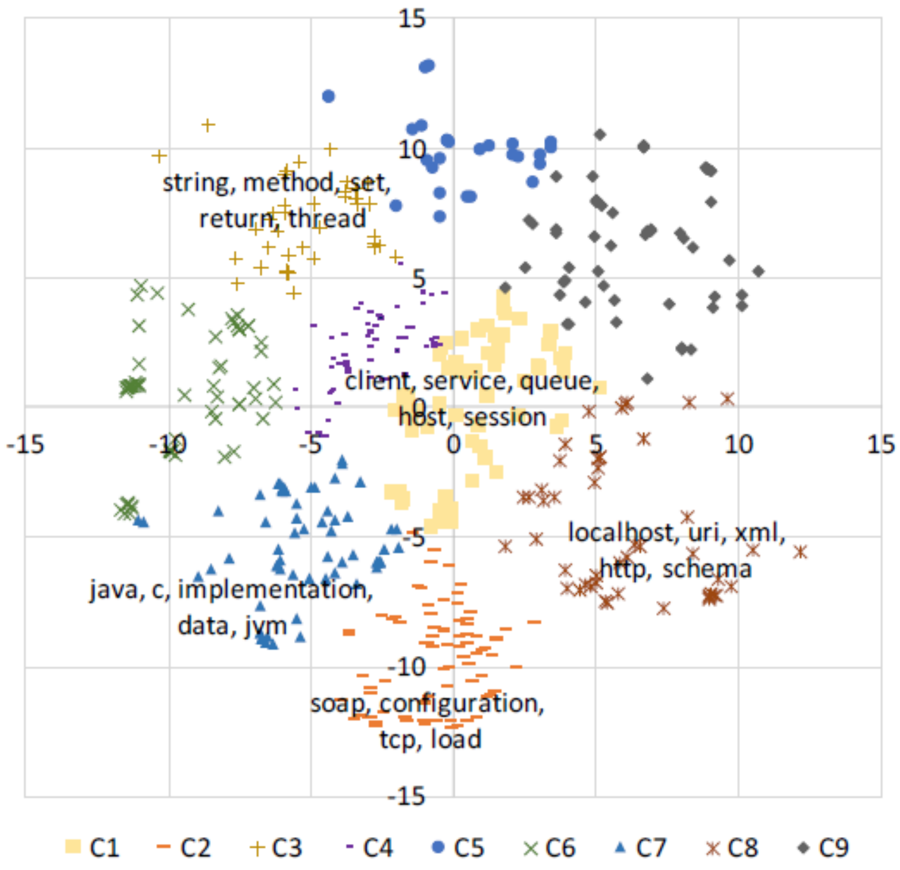
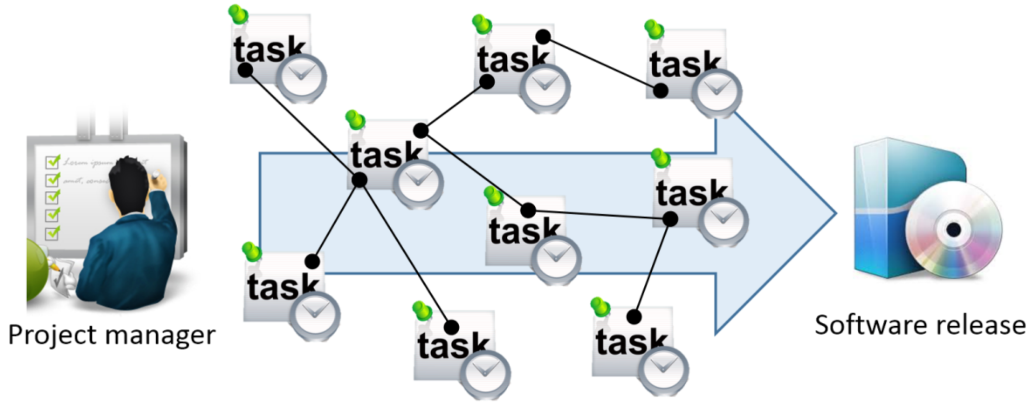
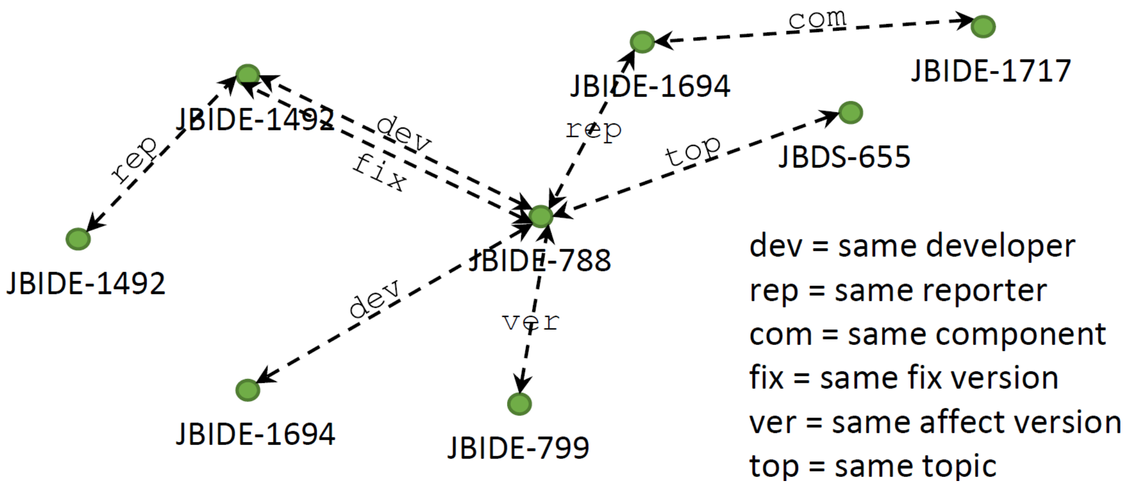


Fig. 4. Top-500 word clusters used in the Apache's issue reports

Proj	Technique	MAE	SA	Proj	Technique	MAE	SA
ME	LD-RNN	**1.02**	**59.03**	JI	LD-RNN	**1.38**	**59.52**
	LSTM+RF	1.08	57.57		LSTM+RF	1.71	49.71
	BoW+RF	1.31	48.66		BoW+RF	2.10	38.34
	Mean	1.64	35.61		Mean	2.48	27.06
	Median	1.73	32.01		Median	2.93	13.88
UG	LD-RNN	**1.03**	**52.66**	MD	LD-RNN	**5.97**	**50.29**
	LSTM+RF	1.07	50.70		LSTM+RF	9.86	17.86
	BoW+RF	1.19	45.24		BoW+RF	10.20	15.07
	Mean	1.48	32.13		Mean	10.90	9.16
	Median	1.60	26.29		Median	7.18	40.16
AS	LD-RNN	**1.36**	**60.26**	DM	LD-RNN	**3.77**	**47.87**
	LSTM+RF	1.62	52.38		LSTM+RF	4.51	37.71
	BoW+RF	1.83	46.34		BoW+RF	4.78	33.84
	Mean	2.08	39.02		Mean	5.29	26.85
	Median	1.84	46.17		Median	4.82	33.38
AP	LD-RNN	**2.71**	**42.58**	MU	LD-RNN	**2.18**	**40.09**
	LSTM+RF	2.97	37.09		LSTM+RF	2.23	38.73
	BoW+RF	2.96	37.34		BoW+RF	2.31	36.64
	Mean	3.15	33.30		Mean	2.59	28.82
	Median	3.71	21.54		Median	2.69	26.07

TASK DEPENDENCY IN SOFTWARE PROJECT (CHOETKIERTIKUL ET AL, WORK IN PROGRESS)

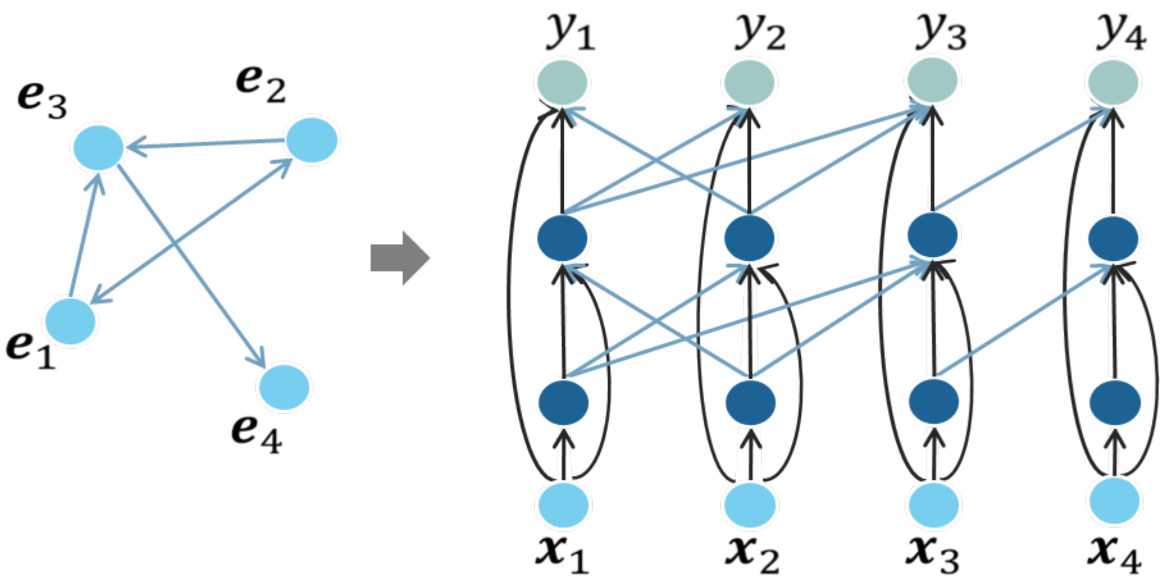




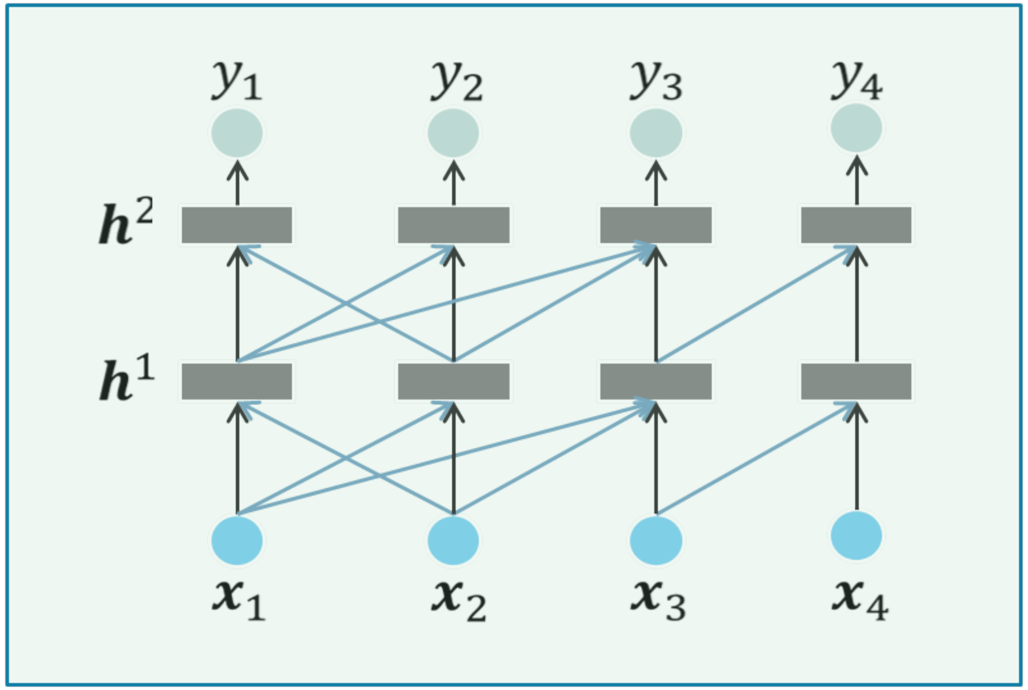
Approximately, one-third of IT projects went over the scheduled time

82% software projects missed schedules

TASK DEPENDENCY IN SOFTWARE PROJECT (MORE ON PART III)



Stacked Inference



Column networks

INFORMATION RETRIEVAL

KEY PROBLEM: RANKING

- Raking web documents in search engines
- Movie recommendation
- Advertisement placement
- Tag recommendation
- Expert finding in a community network
- Friend ranking in a social network
- ???

LEARNING-TO-RANK

Learn to rank responses to a query

A ML approach to Information Retrieval

- Instead of hand-engineering similarity measures, learn it

Two key elements

- Choice model → rank loss (how right/wrong is a ranked list?)
- Scoring function → mapping features into score (how good is the choice?)

- Web documents in search engines
  - query: *keywords*
- Movie recommendation
  - query: *an user*
- Advertisement placement
  - query: *a Web page*
- Tag recommendation
  - query: *a web object*
- Friend ranking in a social network
  - query: *an user*

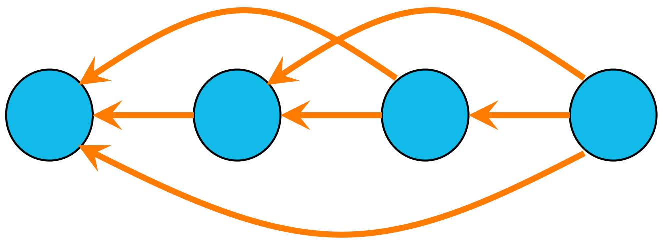
CHOICE BY ELIMINATION

Forward selection does not fit competitive situations

- Sport tournament, grant selection

Choice by elimination:

- Given a set of items with associated utility
- For each step, identify the worst item and remove it
- Repeat until one item is left
- Rank the items by the reverse order of removal



$$P(\boldsymbol{\pi}) = Q(\pi_N) \prod_{i=1}^{N-1} Q(\pi_i \mid \boldsymbol{\pi}_{i+1:N})$$

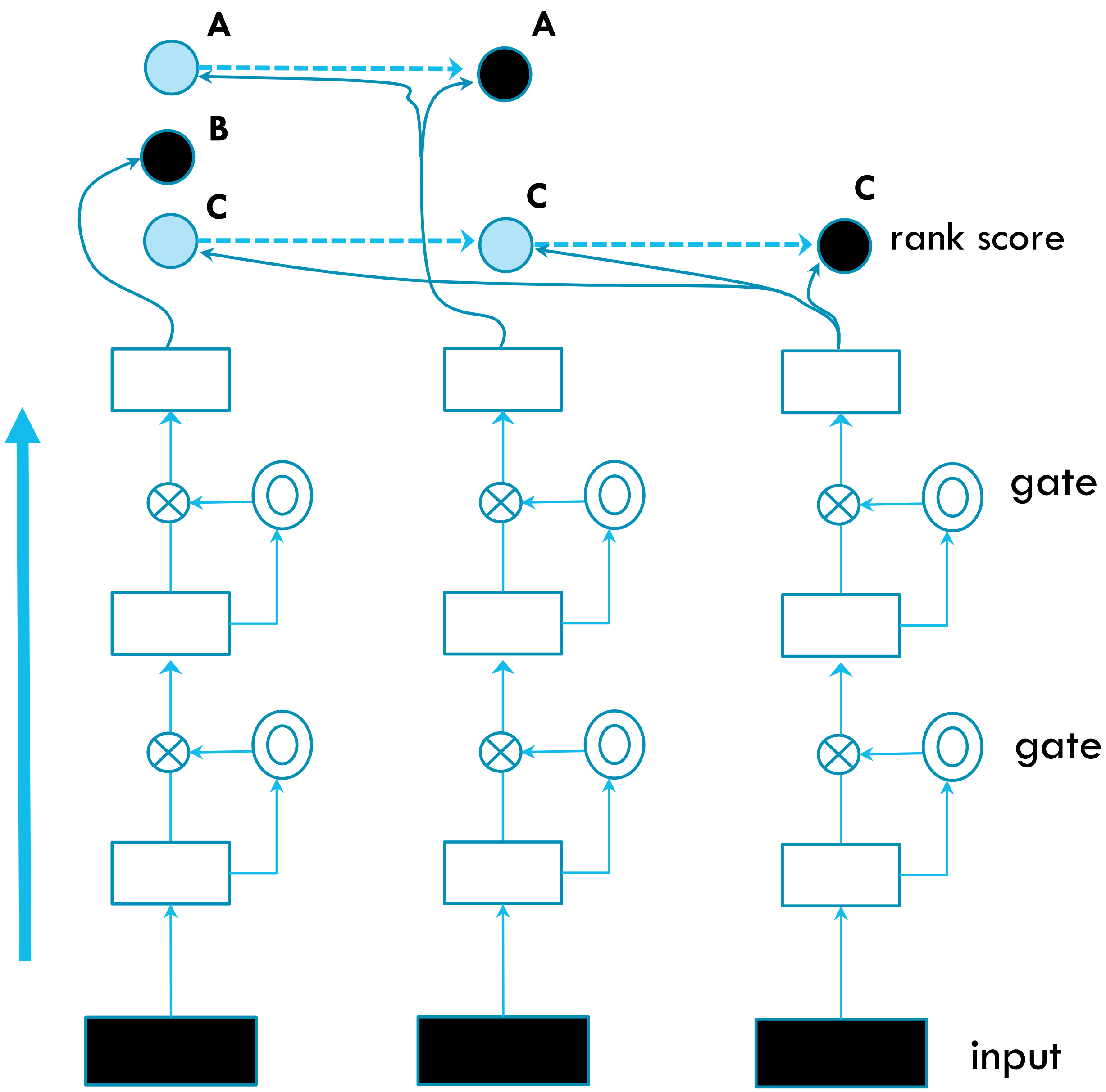
$$Q(\pi_i|\boldsymbol{\pi}_{i+1:N}) = \frac{\exp\left(-f(x_{\pi_i})\right)}{\sum_{j=1}^{i} \exp\left(-f(x_{\pi_j})\right)}$$

HIGHWAY NETS FOR RANKING

The networks represent the scoring function

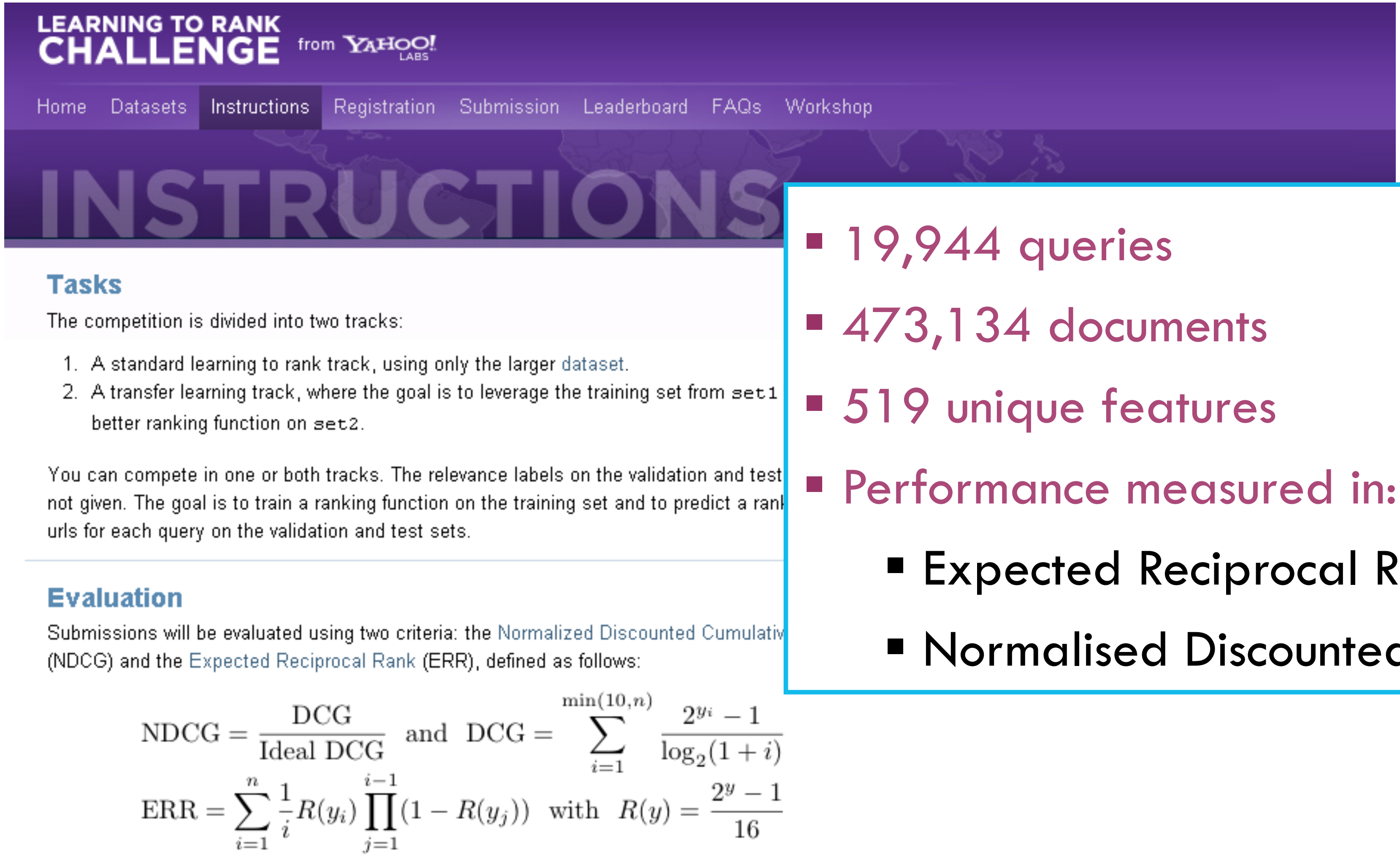
All networks are linked through the rank loss – neural choice by elimination

It is a structured output problem (permutation)



Parameter-tying highway networks

YAHOO! L2R CHALLENGE (2010)


LEARNING TO RANK CHALLENGE from YAHOO! LABS

Home Datasets Instructions Registration Submission Leaderboard FAQs Workshop

INSTRUCTIONS

Tasks

The competition is divided into two tracks:

1. A standard learning to rank track, using only the larger dataset.
2. A transfer learning track, where the goal is to leverage the training set from `set1` ... better ranking function on `set2`.

You can compete in one or both tracks. The relevance labels on the validation and test ... not given. The goal is to train a ranking function on the training set and to predict a rank... urls for each query on the validation and test sets.

Evaluation

Submissions will be evaluated using two criteria: the Normalized Discounted Cumulativ... (NDCG) and the Expected Reciprocal Rank (ERR), defined as follows:

$$\mathrm{NDCG} = \frac{\mathrm{DCG}}{\mathrm{Ideal\ DCG}} \quad \text{and} \quad \mathrm{DCG} = \sum_{i=1}^{\min(10,n)} \frac{2^{y_i}-1}{\log_2(1+i)}$$

$$\mathrm{ERR} = \sum_{i=1}^{n} \frac{1}{i} R(y_i) \prod_{j=1}^{i-1} (1 - R(y_j)) \quad \text{with} \quad R(y) = \frac{2^y - 1}{16}$$

- 19,944 queries
- 473,134 documents
- 519 unique features
- Performance measured in:
  - Expected Reciprocal Rank (ERR)
  - Normalised Discounted Cumulative Gain (NDCG)

RESULTS

As of 2011 – Forward selection + quadratic rank function

	ERR	NDCG@1	NDCG@5
Rank Regress	0.4882	0.683	0.6672
RankNet	0.4919	0.6903	0.6698
Ranking SVM	0.4868	0.6797	0.6662
ListMLE	0.4955	0.6993	0.6705
PairTies-D	0.4941	0.6944	0.6725
PairTies-RK	0.4946	0.6970	0.6716
PMOP-FD	0.5038	0.7137	0.6762
PMOP-Gibbs	0.5037	0.7105	**0.6792**
PMOP-MH	**0.5045**	**0.7139**	0.6790

Rank 41 out of 1500

As of 2016 – Backward elimination + deep nets

	Placket-Luce			Choice by elimination		
Rank function	ERR	NDCG@1	NDCG@5	ERR	NDCG@1	NDCG@5
SGTB	0.497	0.697	0.673	0.506	0.705	0.681
Neural nets	**0.501**	**0.705**	**0.688**	**0.509**	**0.719**	**0.697**

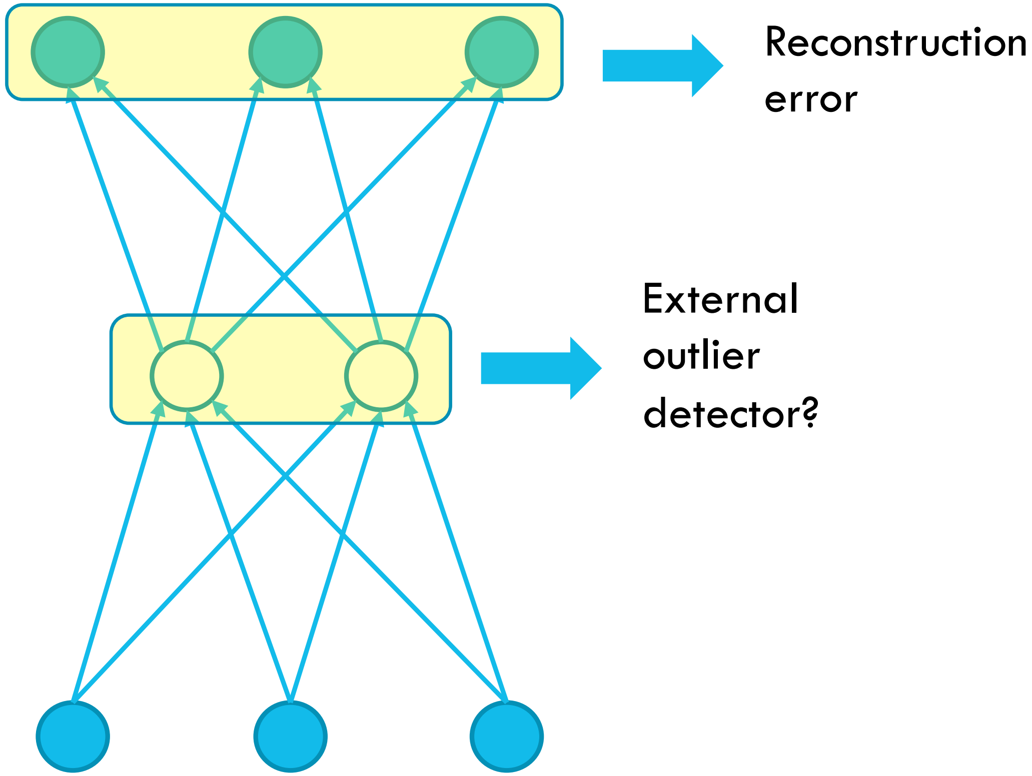
Rank?

dbta.com

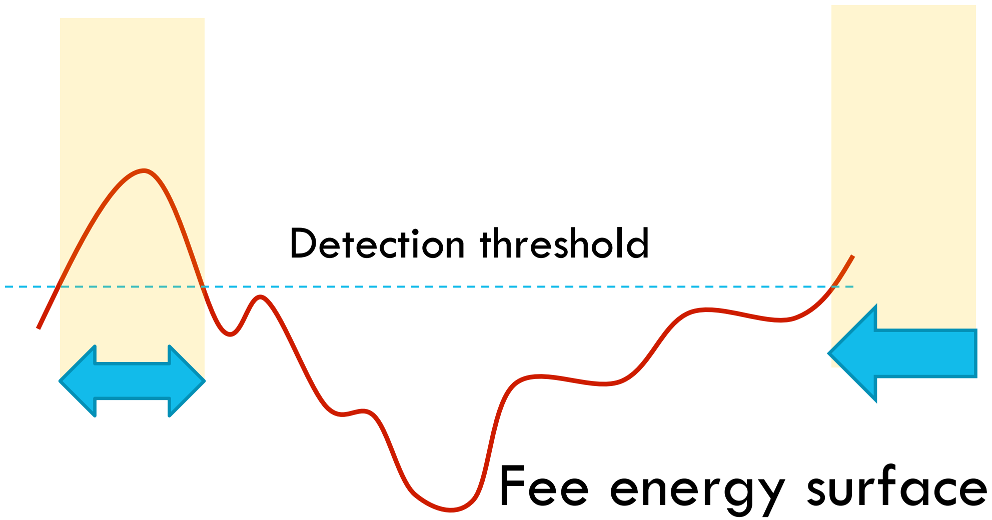
ANOMALY DETECTION USING UNSUPERVISED LEARNING (PART III)

This work is partially supported by the Telstra-Deakin Centre of Excellence in Big Data and Machine Learning

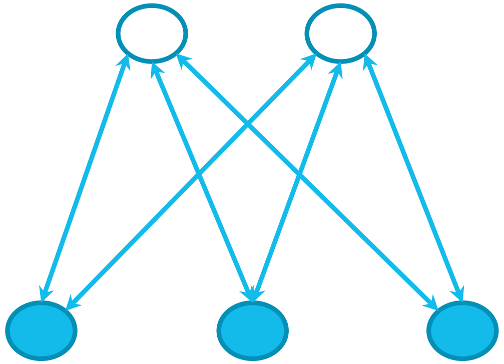
DETECTION METHODS



Auto-encoder (deterministic)



$$F(\boldsymbol{x}) = -\sum_i \left(a_i x_i + \sum_k \log(1 + \exp(x_i W_{ik} + b_k)) \right)$$

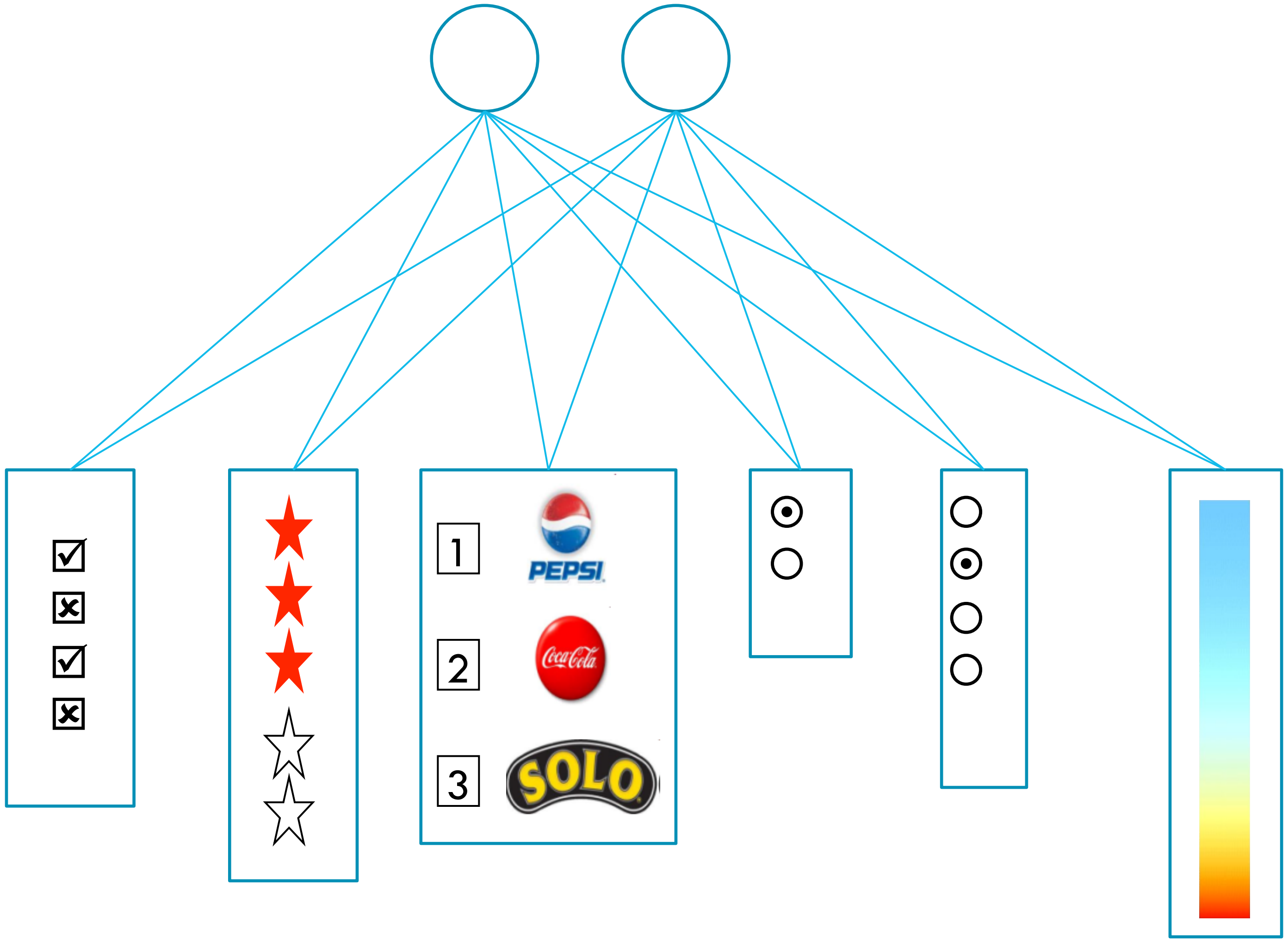


Restricted Boltzmann Machine (probabilistic)

MIXED DATA

	A	B	C	D	E	F	G	H	I	J
1	Age	Sex	Chest pain type	Resting blood pressure	Serum cholestoral (mg/dl)	Fasting blood sugar > 120 mg/dl ?	Resting electrocardiographic result	Maximum heart rate achieved	Exercise induced angina	oldpeak = ST depression induced by exercise relative to rest
2	70	male	asymptomatic (4)	130.0	322.0	no	2	109.0	no	2.4
3	67	female	non-anginal pain (3)	115.0	564.0	no	2	160.0	no	1.6
4	57	male	atypical angina (2)	124.0	261.0	no	0	141.0	no	0.3
5	64	male	asymptomatic (4)	128.0	263.0	no	0	105.0	yes	0.2
6	74	female	atypical angina (2)	120.0	269.0	no	2	121.0	yes	0.2
7	65	male	asymptomatic (4)	120.0	177.0	no	0	140.0	no	0.4
8	56	male	non-anginal pain (3)	130.0	256.0	yes	2	142.0	yes	0.6
9	59	male	asymptomatic (4)	110.0	239.0	no	2	142.0	yes	1.2
10	60	male	asymptomatic (4)	140.0	293.0	no	2	170.0	no	1.2
11	63	female	asymptomatic (4)	150.0	407.0	no	2	154.0	no	4.0
12	59	male	asymptomatic (4)	135.0	234.0	no	0	161.0	no	0.5
13	53	male	asymptomatic (4)	142.0	226.0	no	2	111.0	yes	0.0
14	44	male	non-anginal pain (3)	140.0	235.0	no	2	180.0	no	0.0
15	61	male	typical angina (1)	134.0	234.0	no	0	145.0	no	2.6
16	57	female	asymptomatic (4)	128.0	303.0	no	2	159.0	no	0.0
17	71	female	asymptomatic (4)	112.0	149.0	no	0	125.0	no	1.6
18	46	male	asymptomatic (4)	140.0	311.0	no	0	120.0	yes	1.8
19	53	male	asymptomatic (4)	140.0	203.0	yes	2	155.0	yes	3.1
20	64	male	typical angina (1)	110.0	211.0	no	2	144.0	yes	1.8
21	40	male	typical angina (1)	140.0	199.0	no	0	178.0	yes	1.4
22	67	male	asymptomatic (4)	120.0	229.0	no	2	129.0	yes	2.6

MIXED-VARIATE RBM (TRAN ET AL, 2011)

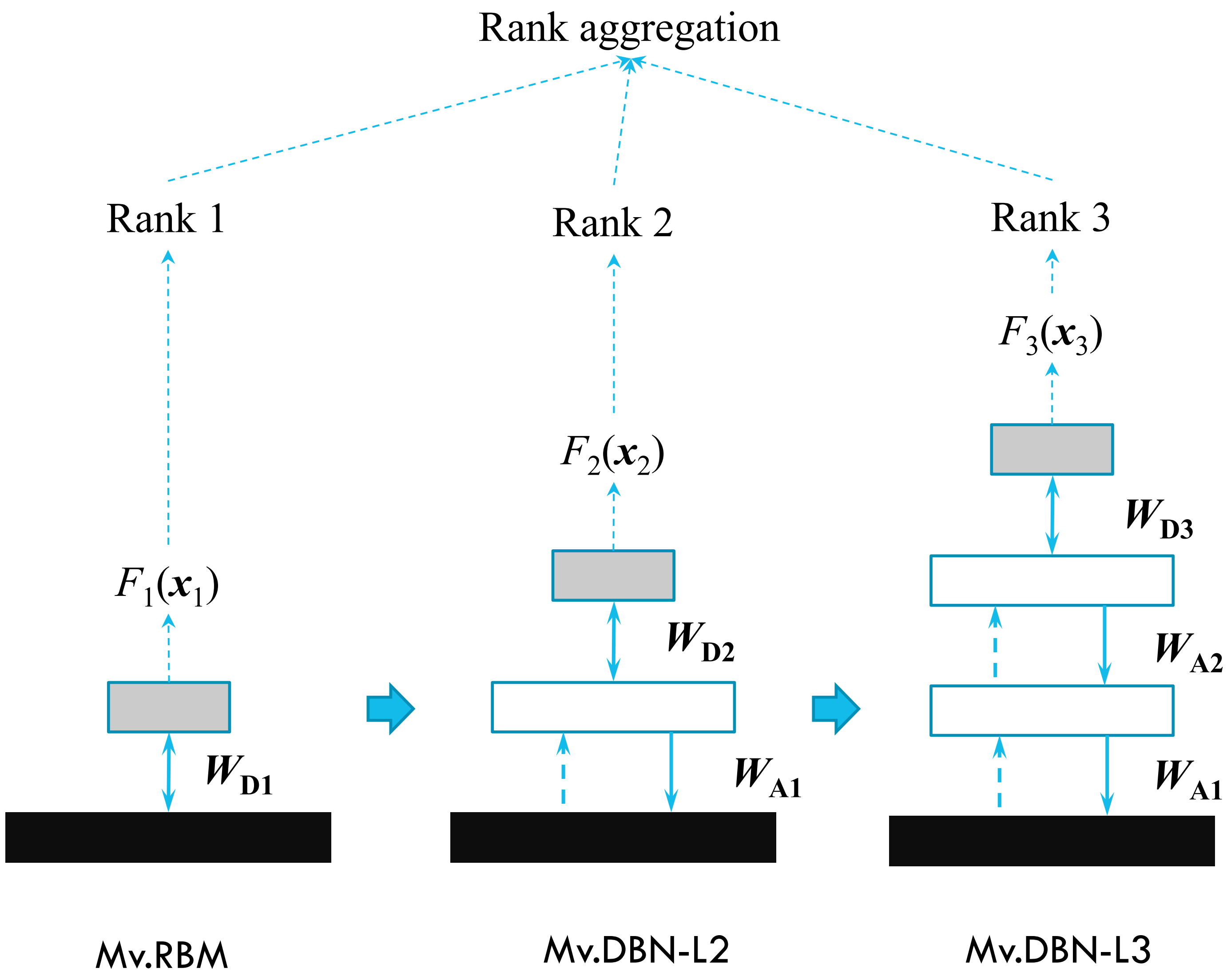


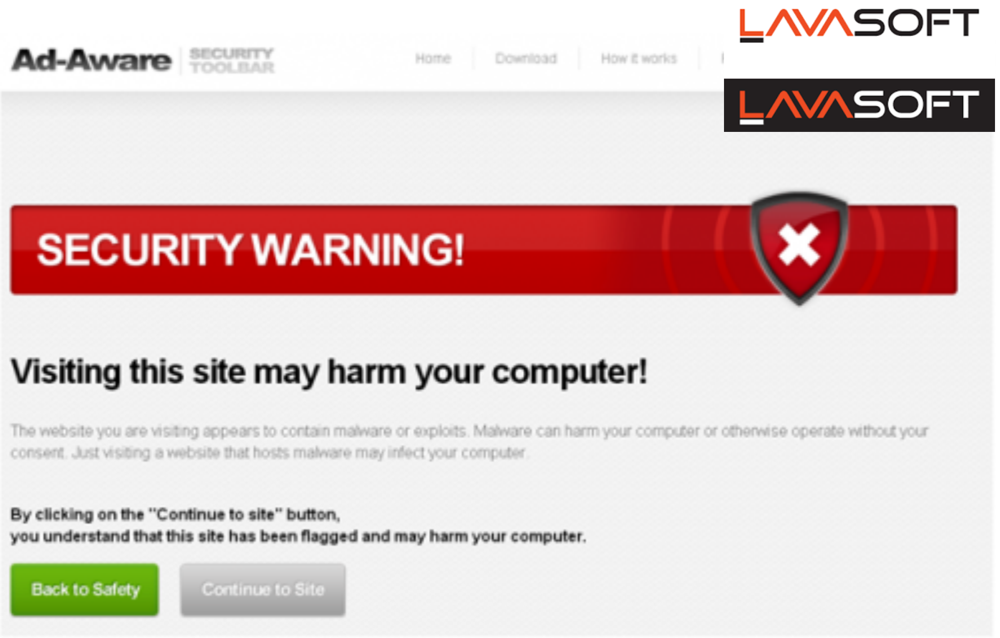
RESULTS OVER REAL DATASETS

Dataset	Single type			mixed-type			
	GMM	OCSVM	PPCA	BMM	ODMAD	GLM-t	Mv.RBM
KDD99-10	0.42	0.54	0.55	–	–	–	**0.71**
Australian Credit	0.74	0.84	0.38	**0.972**	0.942	–	0.90
German Credit	0.86	0.86	0.02	0.934	0.810	–	**0.95**
Heart	0.89	0.76	0.64	0.872	0.630	0.72	**0.94**
Thoracic Surgery	0.71	0.71	0.70	**0.939**	0.879	–	0.90
Auto MPG	**1.00**	**1.00**	0.67	0.625	0.575	0.64	**1.00**
Contraceptive	0.62	0.84	0.02	0.673	0.523	–	**0.91**
Average	*0.75*	*0.79*	*0.43*	*0.84*	*0.73*	*0.68*	***0.91***

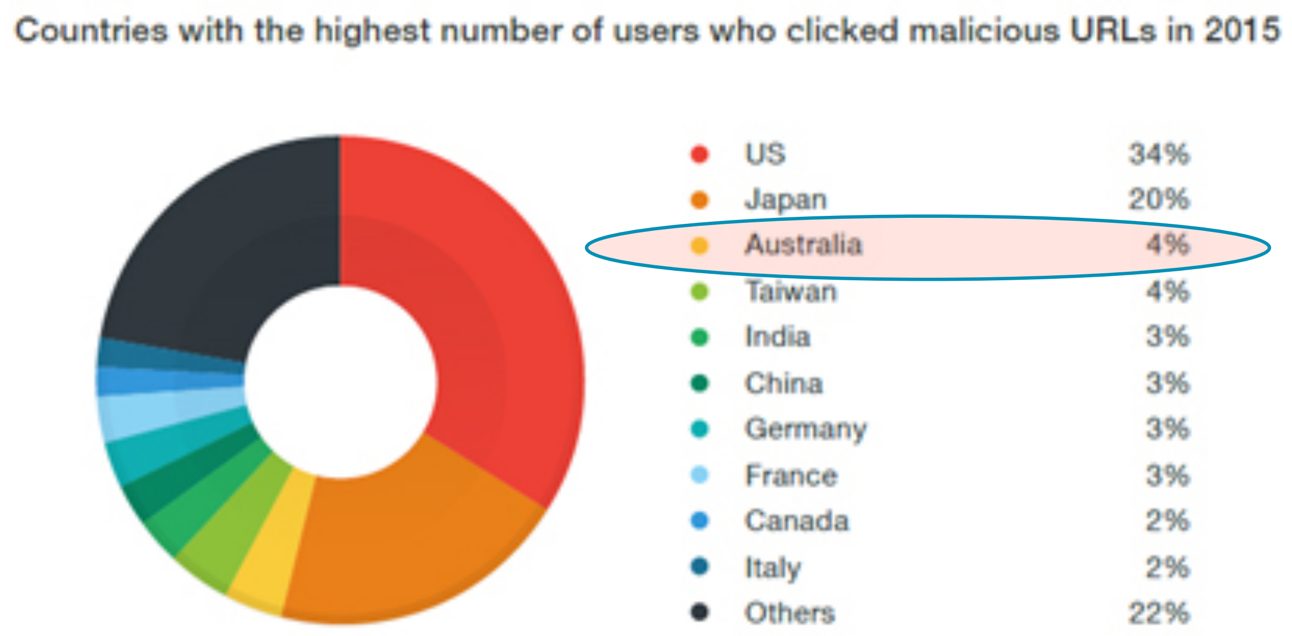
ABNORMALITY ACROSS ABSTRACTIONS

$$\bar{r}_i(p) = \left(\sum_{l=1}^{L} r_{li}^{p} \right)^{1/p}$$





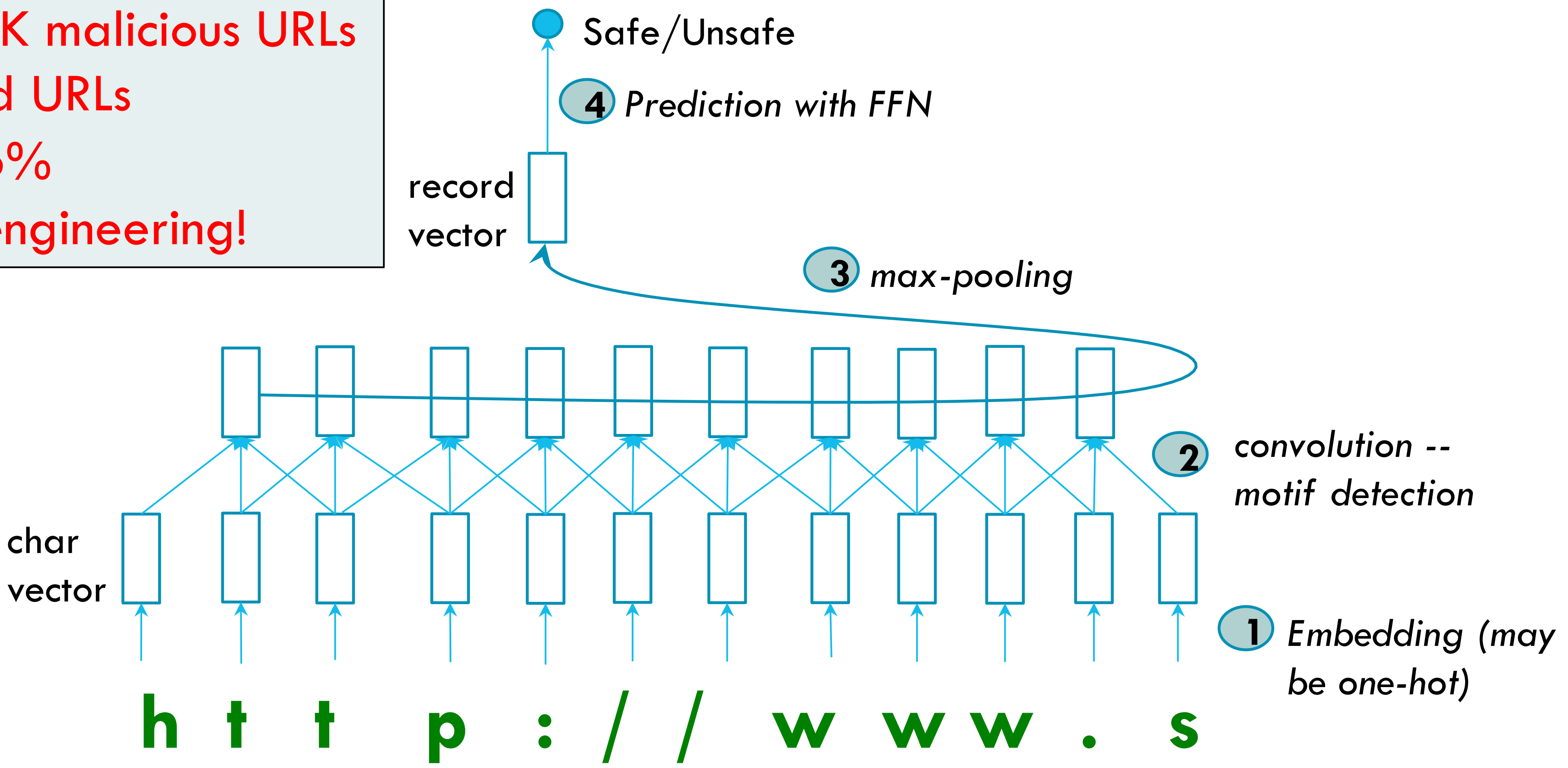
MALICIOUS URL CLASSIFICATION



http://www.indiainfoline.com/article/news-sector-information-technology/india-ranks-4th-in-highest-users-who-clicked-malicious-urls-in-2015-trend-micro-116052700684_1.html

MODEL OF MALICIOUS URLS

Train on 900K malicious URLs
1,000K good URLs
Accuracy: 96%
No feature engineering!



SUMMARY OF PART II

Hand-on:

- Introducing programming frameworks (Theano, TensorFlow, Mxnet)

Domains how-to:

- Healthcare
- Learning to rank objects
- Software engineering
- Anomaly detection
- Malicious URLs

https://duroosullughatilarabiyyah.files.wordpress.com/2010/07/qa.jpg