Text-Aware Predictive Monitoring of Business Processes with LSTM Neural Networks

David Benedikt Georgi
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Interim Presentation

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Business Process Monitoring – A Modern Environment for Commercial Process Mining

Traditional Process Mining

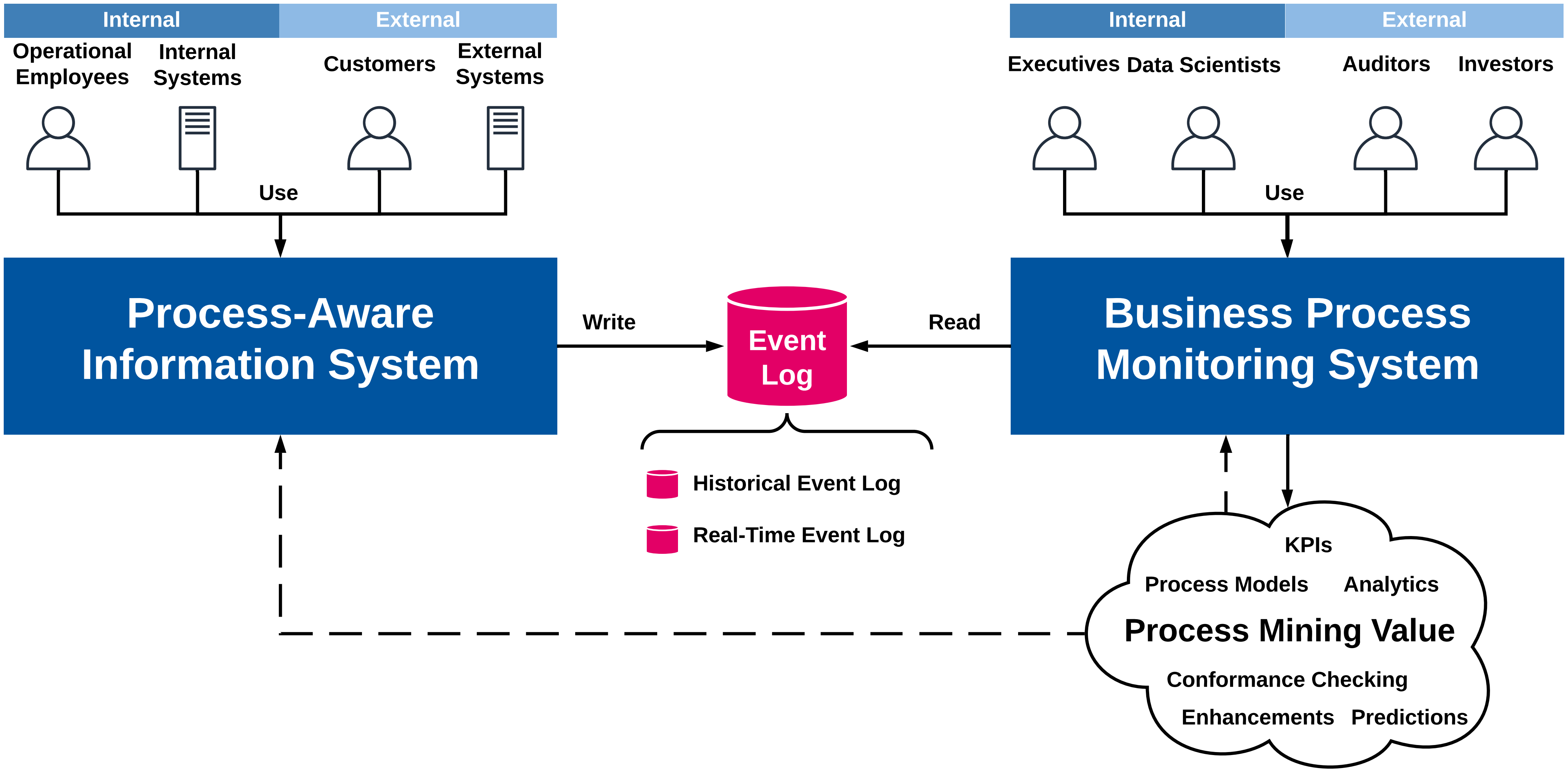
- Applied project-based
- Manual data extraction
- Historical event data only (offline)
- Standalone process mining software

VS.

Process Mining in Business Process Monitoring

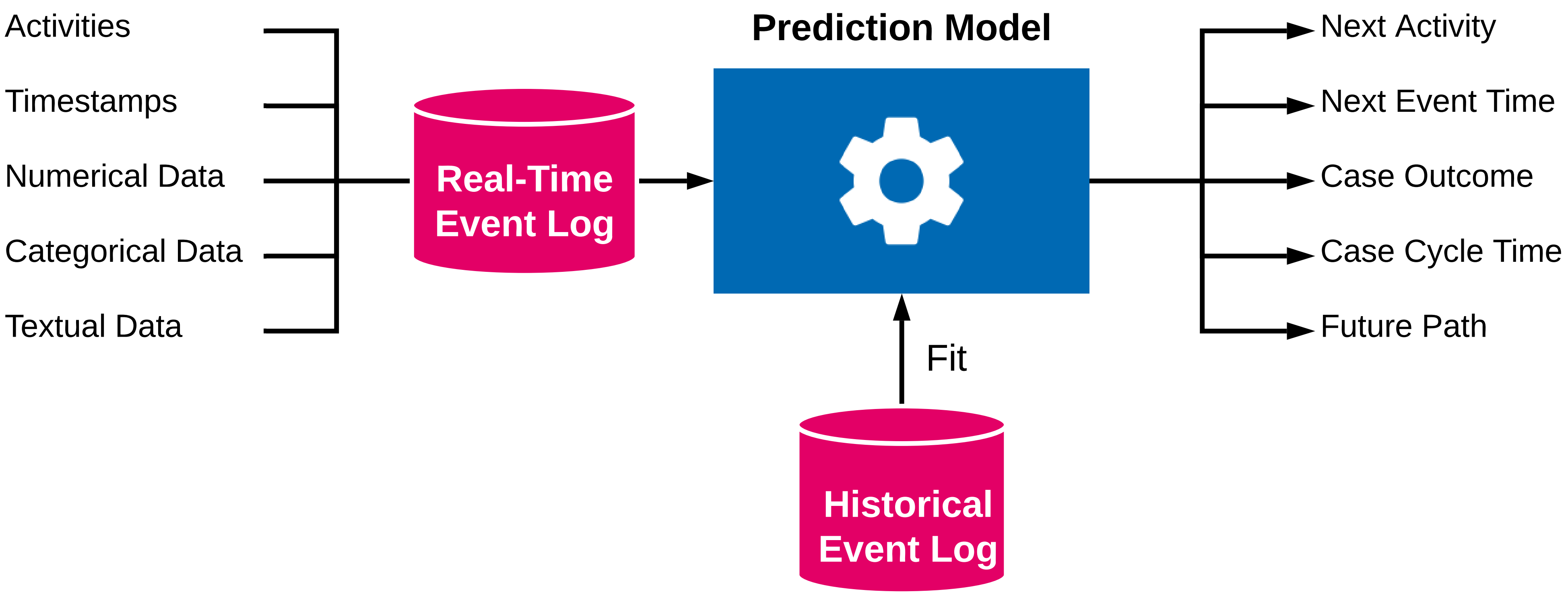
- Applied continuously
- Permanent data connection
- Historical and real-time event data (online)
- Integrated process mining platform

Business Process Monitoring – A Modern Environment for Commercial Process Mining



Motivation: Adding the Forward Perspective to Business Process Monitoring

Knowing the future of a process gives organizations a competitive advantage.



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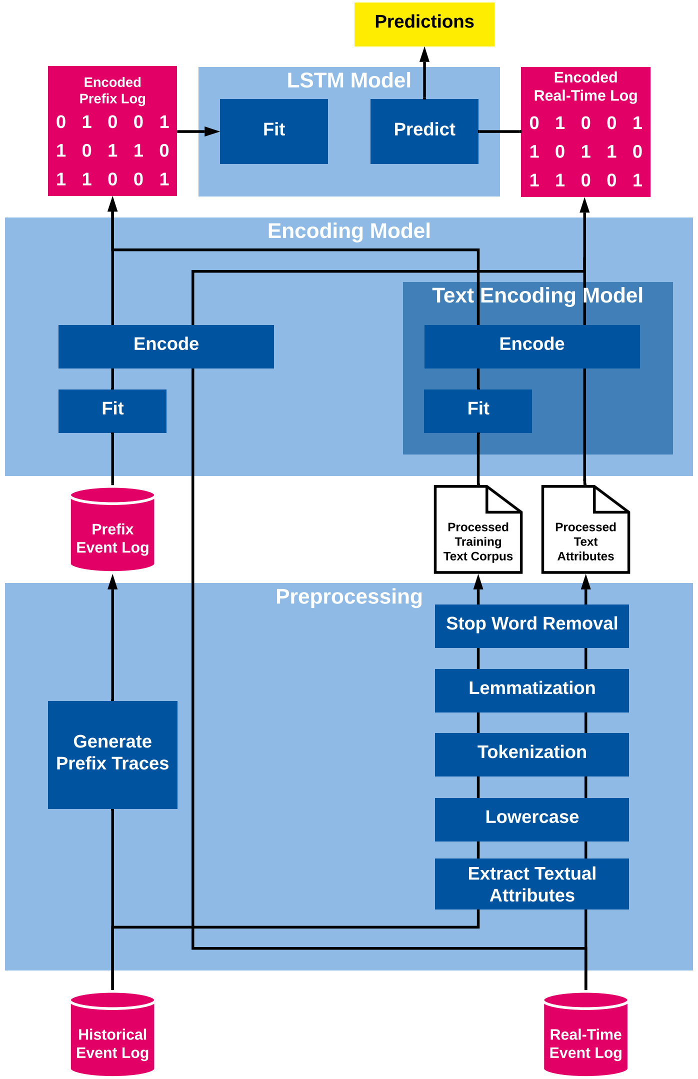
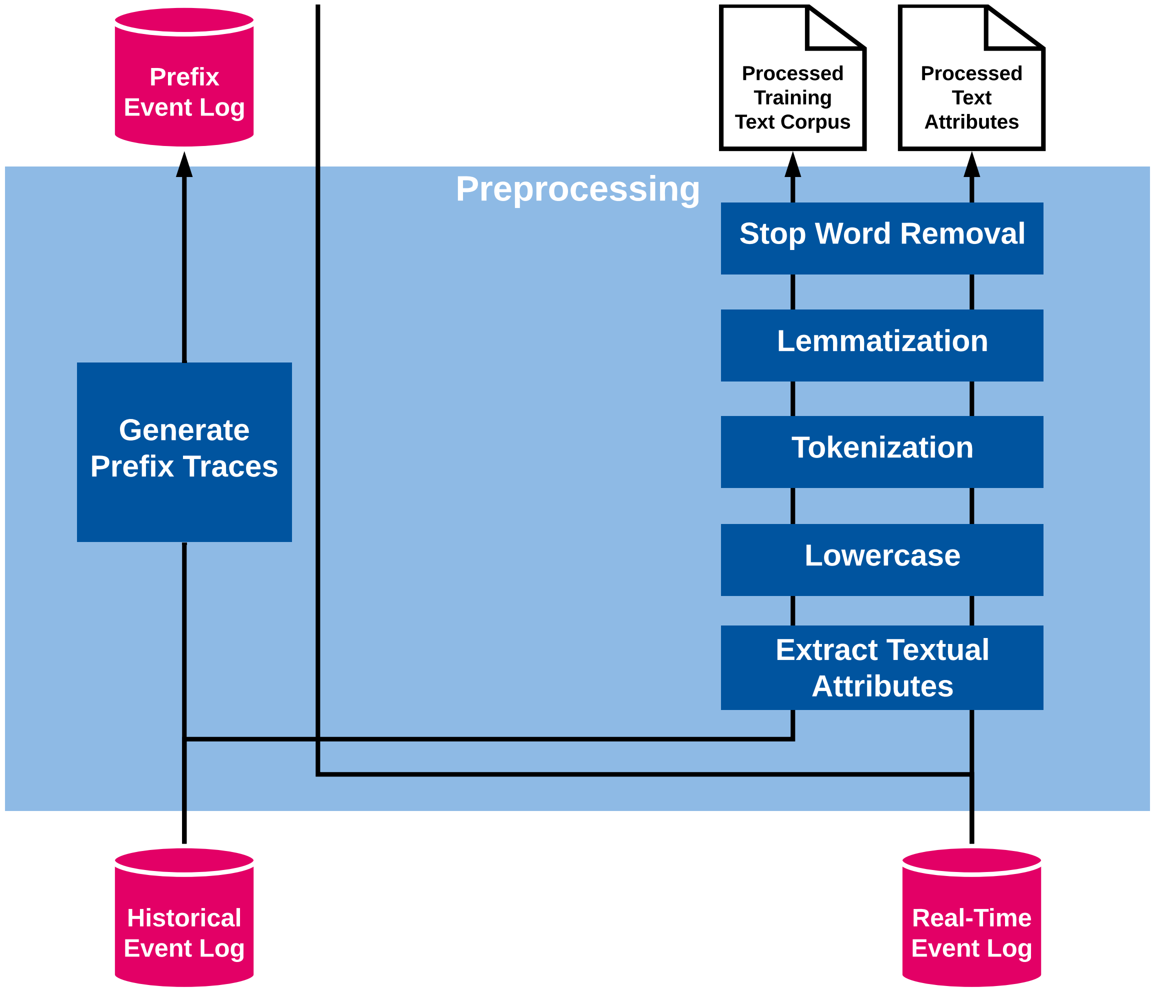
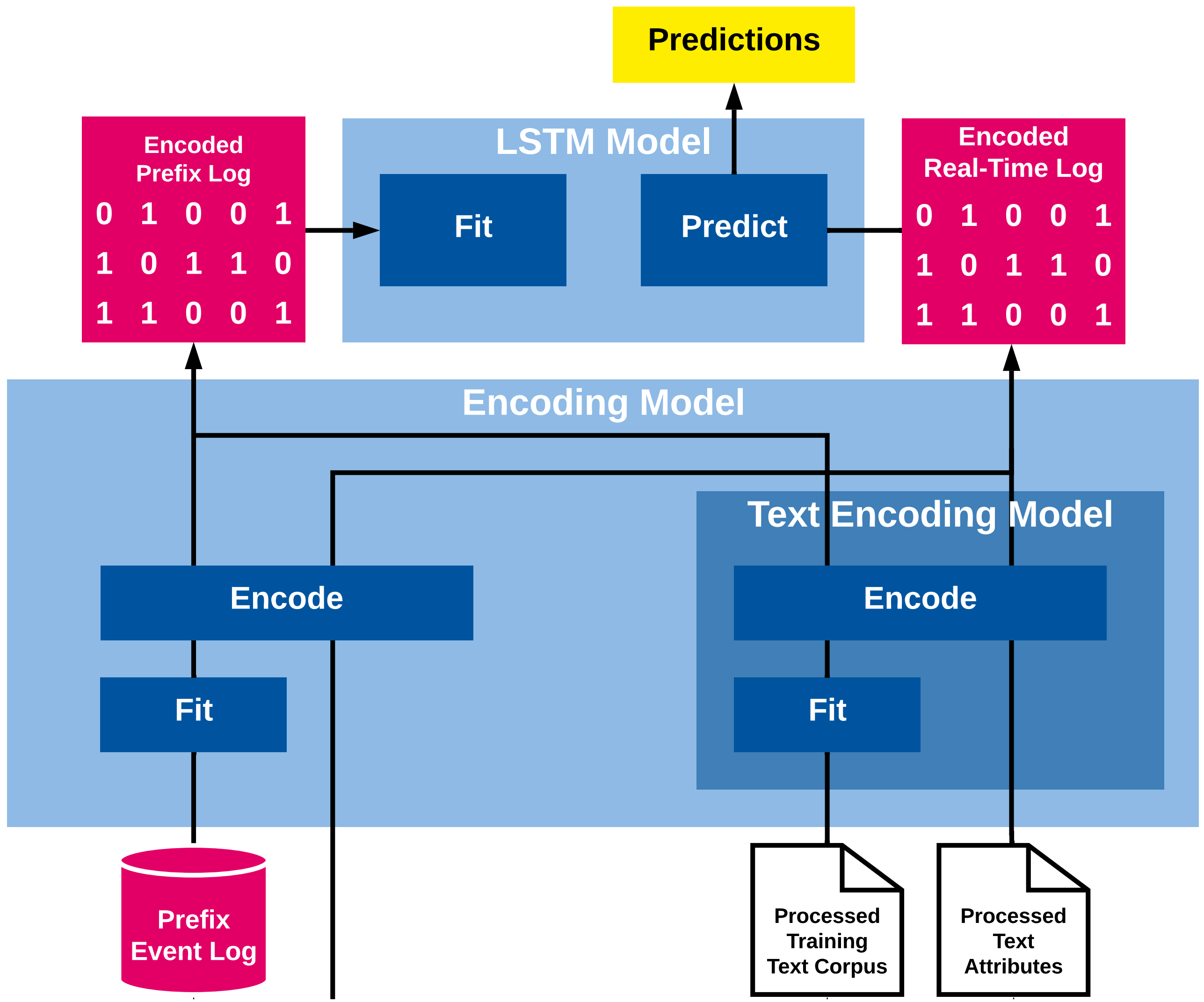
Contribution: A Text-Aware Process Prediction Framework



Contribution: A Text-Aware Process Prediction Framework



Contribution: A Text-Aware Process Prediction Framework



Trace Encoding

Transforming a sequence of events to a sequence of vectors

$$\langle e_1, e_2, e_3, \dots, e_n \rangle \quad \Rightarrow \quad \langle x_1, x_2, x_3, \dots, x_n \rangle$$

$e_i =$

Case ID	Activity	Timestamp	Resource	Cost	Comment
254	Consultation	02.02.2020:18.14	J. Brown, MD	67.24	"The patient has been diagnosed with high blood pressure."

$$x_i = (a_i, t_i, d_i^1, d_i^2, d_i^3)$$

Encoding of Categorical and Numerical Attributes

Activities & Categorical Attributes

1-Hot-Encoding

1-Hot(„Consultation“) $= (0,1,0,0,0)$

Index	Activity
1	Register patient
2	Consultation
3	Blood test
4	MRI
5	Release Patient

Numerical Attributes

Normalization

$$\hat{d} = \frac{d \ - \min(d)}{\max(d) - \min(d)}$$

Capturing Temporal Dependencies

Encoding of timestamp data

- 6-dimensional vector with time-based features is part of every encoded event
- Capture daily, weekly, seasonal dependencies and concept drifts
- **Idea:** Process behavior might be influenced by office hours, weekends, seasons, etc.
- All time features are normalized to [0,1]

Feature	Description
t_i^1	Time since previous event
t_i^2	Time since case start
t_i^3	Time since first recorded event
t_i^4	Time since midnight
t_i^5	Time since last Monday
t_i^6	Time since last January 1 00:00

$$t_i = (t_i^1, t_i^2, t_i^3, t_i^4, t_i^5, t_i^6)$$

Text Vectorization

1. Step: Text Normalization

Transformation	Example
Original	"The patient has been diagnosed with high blood pressure."
Lowercase	"the patient has been diagnosed with high blood pressure."
Tokenization	[“the", "patient", "has", "been", "diagnosed", "with", "high", "blood", "pressure", ".”]
Lemmatization	["the", "patient", "have", "be", "diagnose", "with", "high", "blood", "pressure", "."]
Stop word filtering	["patient", "diagnose", "high", "blood", "pressure”]

Text Vectorization – 4 Approaches

2. Step: Apply Text Model

Bag of Words	Bag of N-Gram
Paragraph Vector	Latent Dirichlet Allocation

Bag of Words

- Represent documents by the **term frequencies** (tf) of its words
- Construct **vocabulary** using the historical event log
- Create vector with size of the vocabulary with the term frequencies of the words
- Normalize each component with the **inversed document frequency** (idf)

Example:

Vocabulary

Index	Word
1	patient
2	urgent
3	blood
4	pressure
5	notice
6	leg
7	high
8	low

Document

["patient", "diagnose", "high", "blood", "pressure”]

↓

(1, 0, 1, 1, 0, 0, 1, 0)

↓

(0.5, 0, 0.4, 1.2, 0, 0, 1.4, 0)

Bag of N-Gram

- Represent documents by the **term frequencies** (tf) of its n-grams
- Construct **n-gram-vocabulary** using the historical event log
- Create vector with size of the vocabulary with the term frequencies of the words
- Normalize each component with the **inversed document frequency** (idf)

Example: 2-Gram

Vocabulary

Index	2-Gram
1	(patient, diagnose)
2	(urgent, quick)
3	(blood, pressure)
4	(value, significant)
5	(notice, recently)
6	(leg, break)
7	(diagnose, high)
8	(high, blood)

Document

["patient", "diagnose", "high", "blood", "pressure”]

↓

[("patient", "diagnose"), ("diagnose", "high"), ("high", "blood") and ("blood", "pressure”)]

↓

(1, 0, 1, 0, 0, 0, 1, 1)

↓

(0.5, 0, 0.4, 0, 0, 0, 1.4, 0.6)

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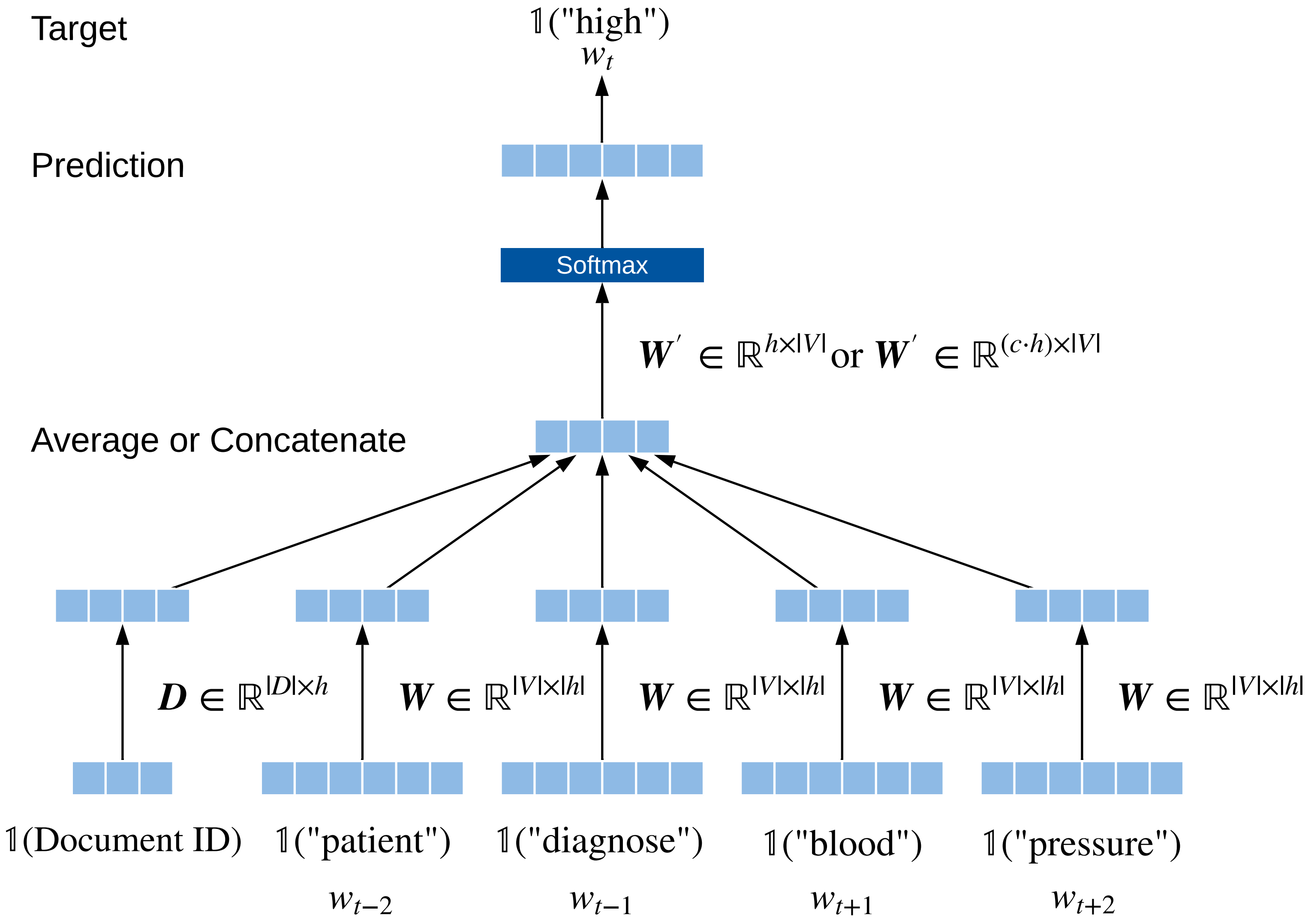
Paragraph Vector



Describe documents as a probability distribution over topics

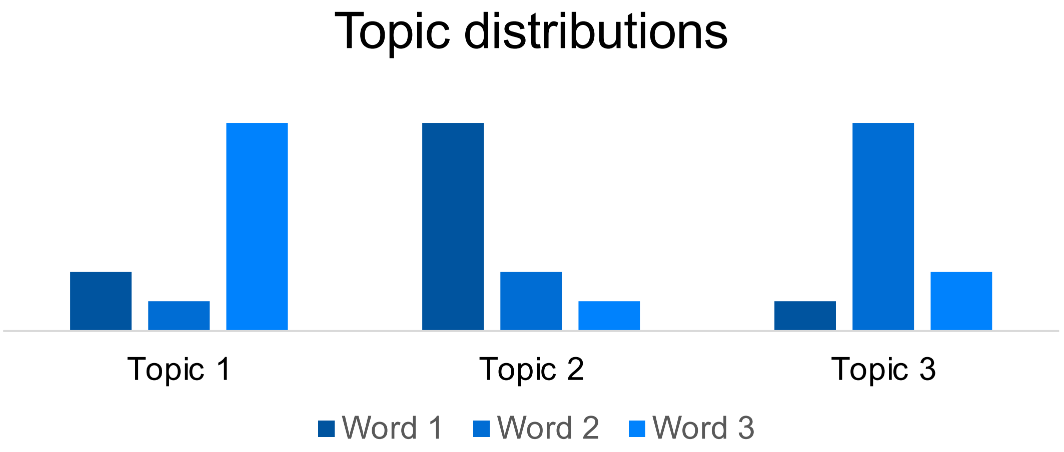
- Document is represented by a vector of dimension *k*, such that component *i* describe the "affiliation" to topic *i*
- Topics are probability distributions over words
- Find the topic distribution for each document that most likely would generate the corresponding document

Example: 3 Topics, 3 Words

Affiliation to topic 2

$$(0.1, \boxed{0.2}, 0.7)$$

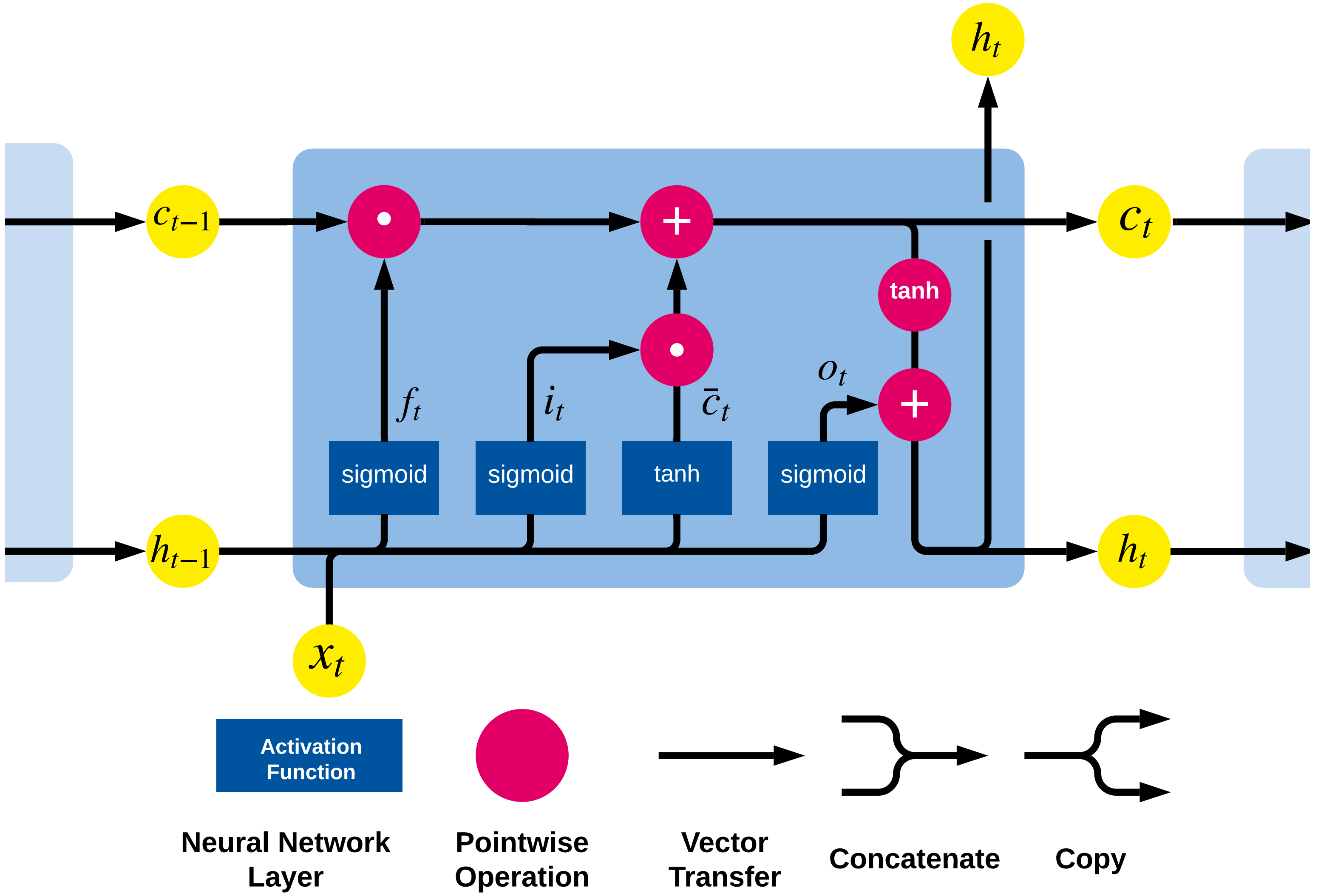
Topic distribution of a document



Text Vectorization – Comparison

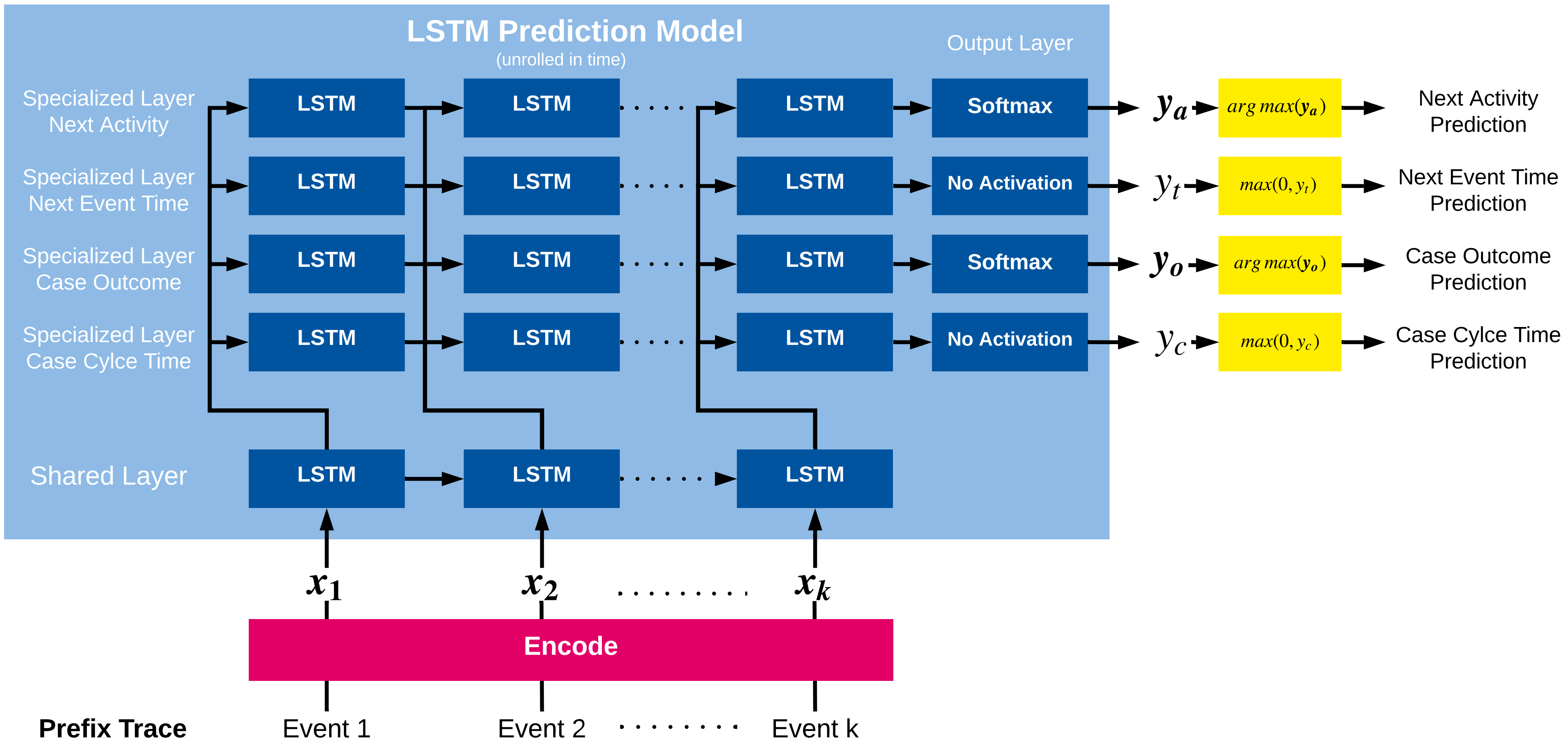
Text Model	Pro	Contra
Bag of Words	• Simple and fast	• Ignores word order • High dimensionality
Bag of N-Gram	• Simple and fast • Considers word order	• Very high dimensionality
Paragraph Vector	• Expressive representation • Low dimensionality	• High computation costs • Requires big training corpus
Latent Dirichlet Allocation	• Low dimensionality	• Ignores word order • Choice of number of topics is difficult

LSTM Module



h_t
c_{t-1}
c_t
h_{t-1}
h_t
x_t
tanh
f_t
i_t
$\bar{c}_t$
o_t
sigmoid
sigmoid
tanh
sigmoid
Activation Function
Neural Network Layer
Pointwise Operation
Vector Transfer
Concatenate
Copy

LSTM Network Architecture



The Next Steps…

Evaluation on real-life event logs

Research Focus:

- Impact of the utilization of textual data
- Impact of the text model choice and other parameters
- Comparison with existing techniques regarding prediction quality

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Thank you
for your attention.

Any questions?