UNSL at eRisk 2022: Decision policies with history for early classification

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Outline

- Early text classification framework
- Proposed models
- Runs and results:
    - Task 1
    - Task 2

https://jmloyola.github.io/files/talks/2022_erisk.pdf

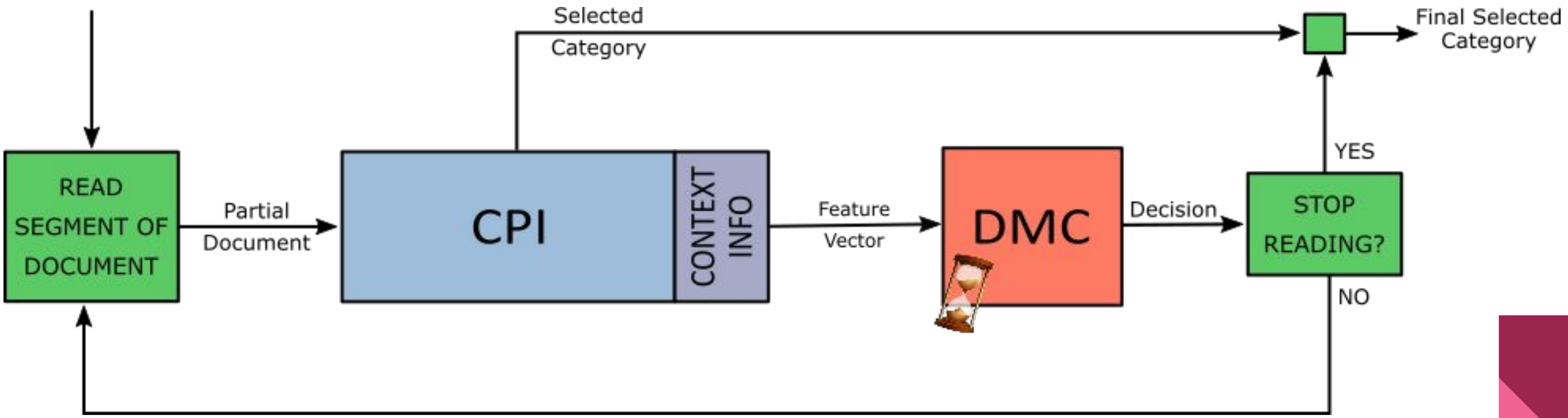
Early Text Classification Framework

Early Text Classification Framework

- Based on the development of predictive models that can determine the category of a document as soon as possible.
- Find an adequate balance between:
  - precision of the classification
  - minimum time for a prediction to be reliable.
- It can be conceptualized in two parts:
  - Classification with Partial Information (CPI).
  - Decision of the Moment of Classification (DMC).

Early Text Classification Framework

- CPI → Classification with Partial Information
- DMC → Decision of the Moment of Classification



Early risk detection

- Special case of early text classification.
- We are only concerned with predicting the risk category as early as possible.
- If the current partial input is classified as non-risky, the model continues to accumulate information in case, in the future, the user begins to show risky patterns.
- It is essential to recover as many users at risk as possible as their lives could be in danger.

Proposed Models

Proposed models

- EarlyModel
- SS3
- EARLIEST

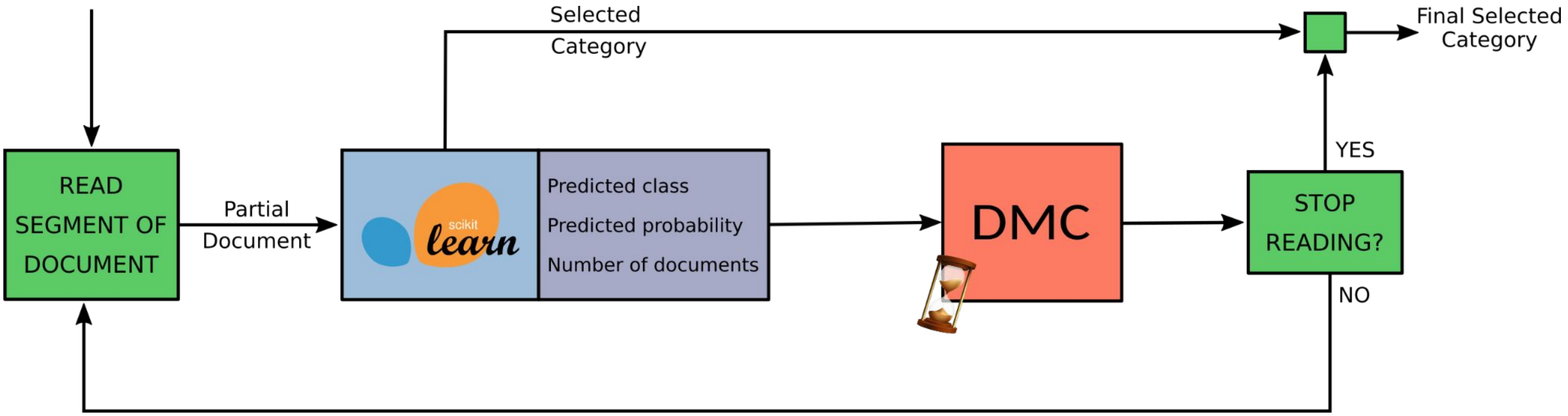
Proposed models

We can identify each model with:

- Input representation
- Model used for classification with partial information (CPI)
- Early alert policy (DMC)

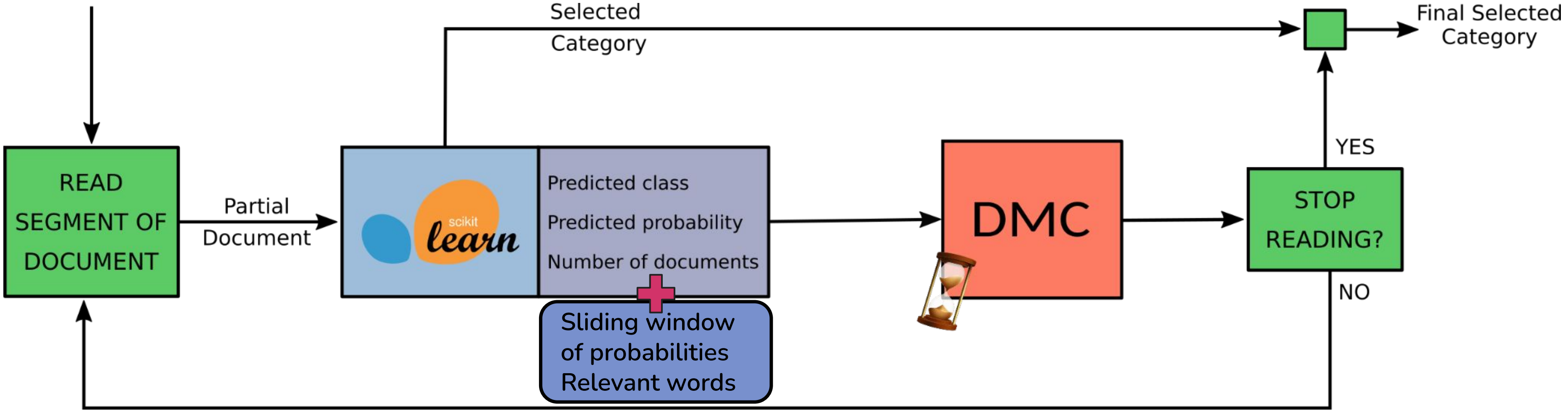
EarlyModel

EarlyModel



Selected
Category
Final Selected
Category
READ
SEGMENT OF
DOCUMENT
Partial
Document
scikit
learn
Predicted class
Predicted probability
Number of documents
DMC
YES
STOP
READING?
NO

EarlyModel



READ SEGMENT OF DOCUMENT
Partial Document
scikit learn
Predicted class
Predicted probability
Number of documents
Sliding window of probabilities
Relevant words
Selected Category
DMC
STOP READING?
YES
NO
Final Selected Category

EarlyModel

Input representation:

- Bag of words
- Latent Dirichlet Allocation (LDA)
- Latent Semantic Analysis (LSA)
- Doc2vec

EarlyModel

Models used for classification with partial information:

- Decision trees
- K-nearest neighbors
- Support vector machine (SVM)
- Logistic regression
- Multi-layer perceptron (MLP)
- Random forests

- LSTM

- BERT

scikit learn

PyTorch

Transformers

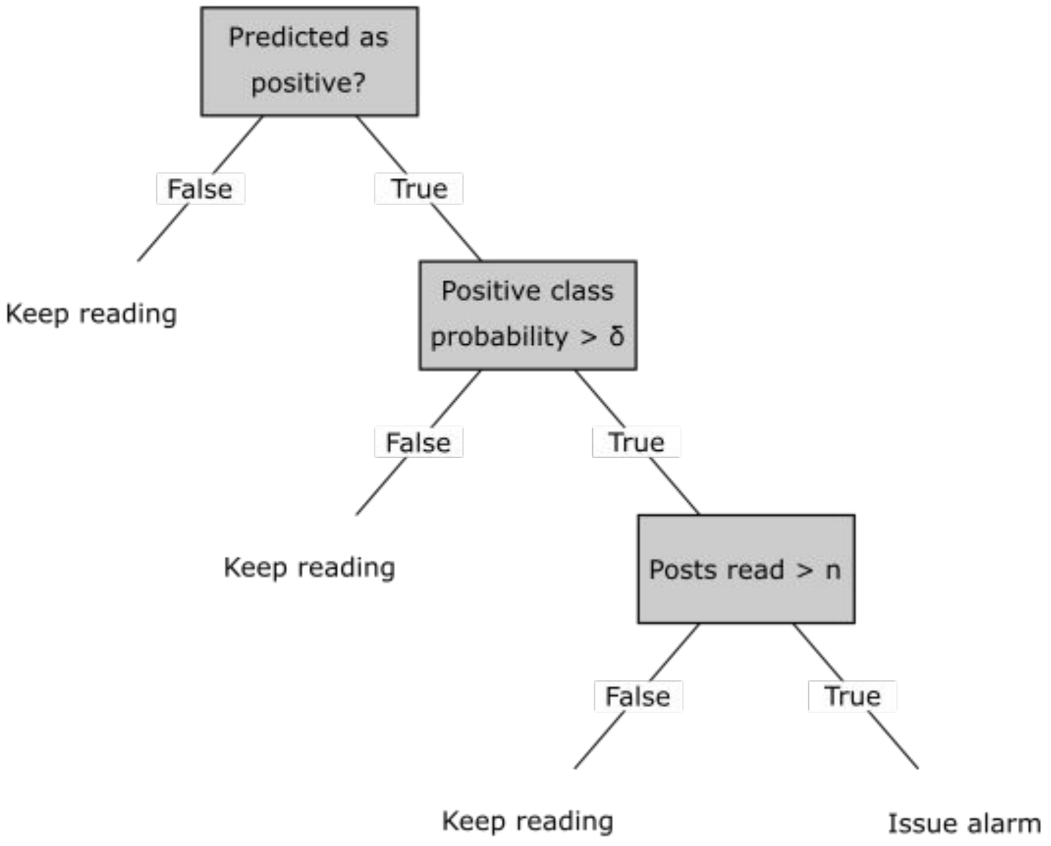
EarlyModel

Stop criteria (Early alert policies):

- Simple Stop Criterion (SSC)
- Historic Stop Criterion (HSC)
- Learned Decision Tree Stop Criterion (LDTSC)

EarlyModel

Simple Stop Criterion (SSC)



EarlyModel

Historic Stop Criterion (HSC)

- Similar to the Simple Stop Criterion, without the model output node.
- We observed that the user probability fluctuates as time progress, surpassing the probability threshold sometimes → increasing the number of false positive.
- Add a moving window of last probabilities for each user.
- If all the probabilities surpass the threshold we emit an alarm.

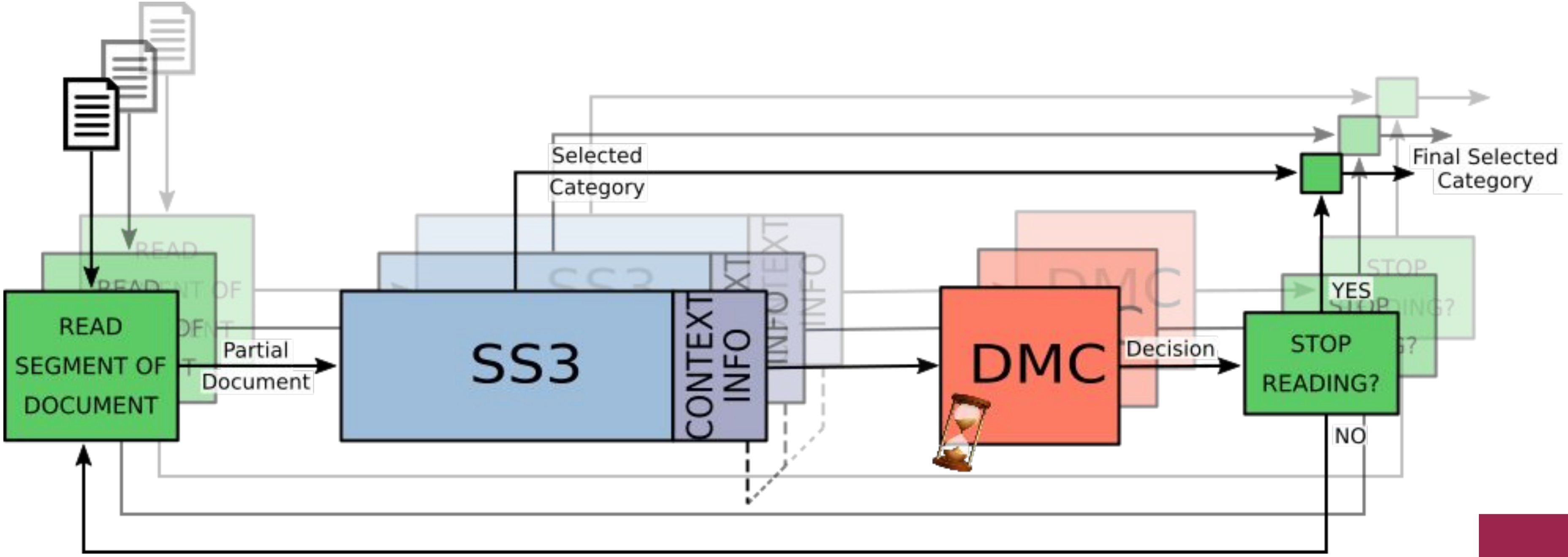
EarlyModel

Learned Decision Tree Stop Criterion (LDTSC)

- Train a Decision Tree on a manually label corpus with the moment to stop the input processing.
- Features used:
  - class probability,
  - average and median of the last probabilities,
  - number of relevant words.

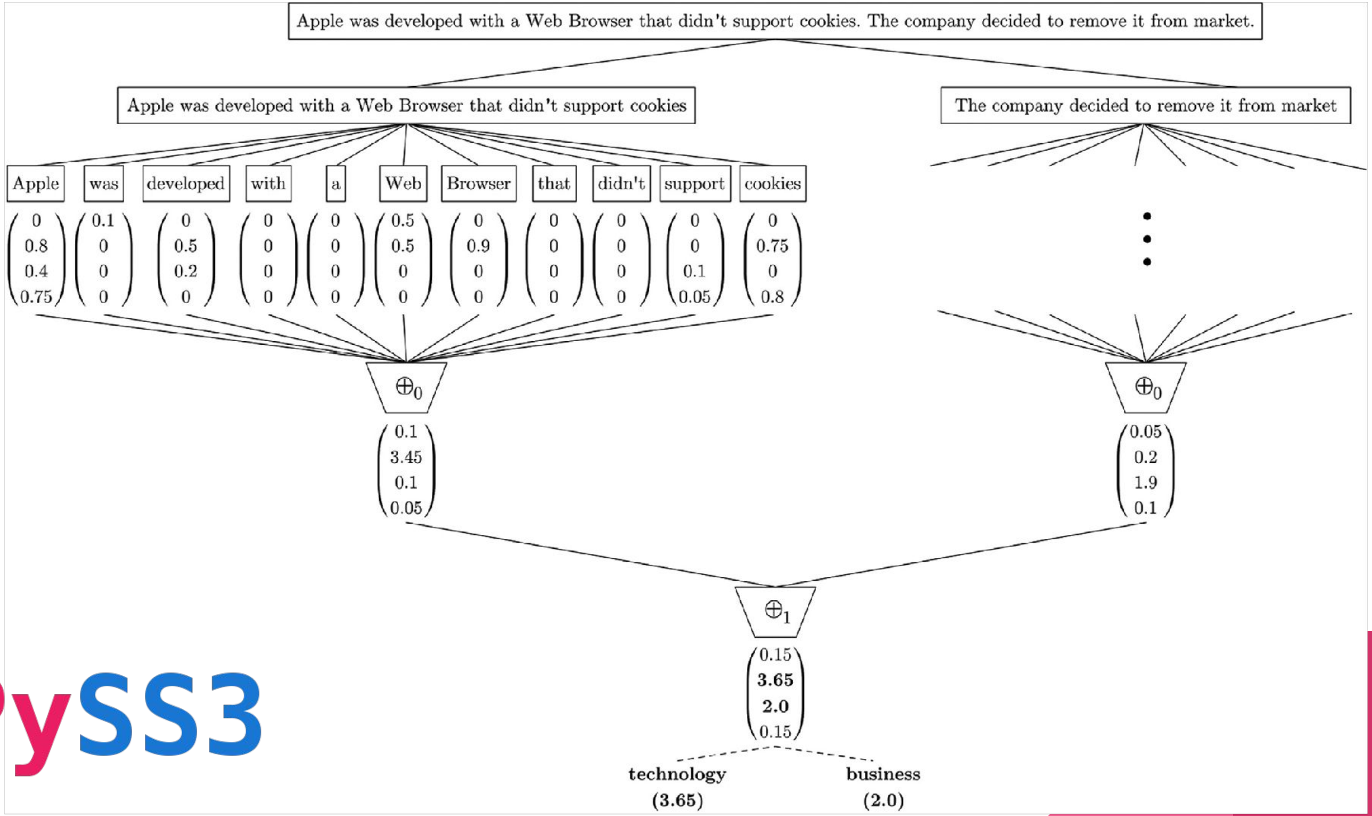
SS3

SS3



Loyola et al. 2021

SS3

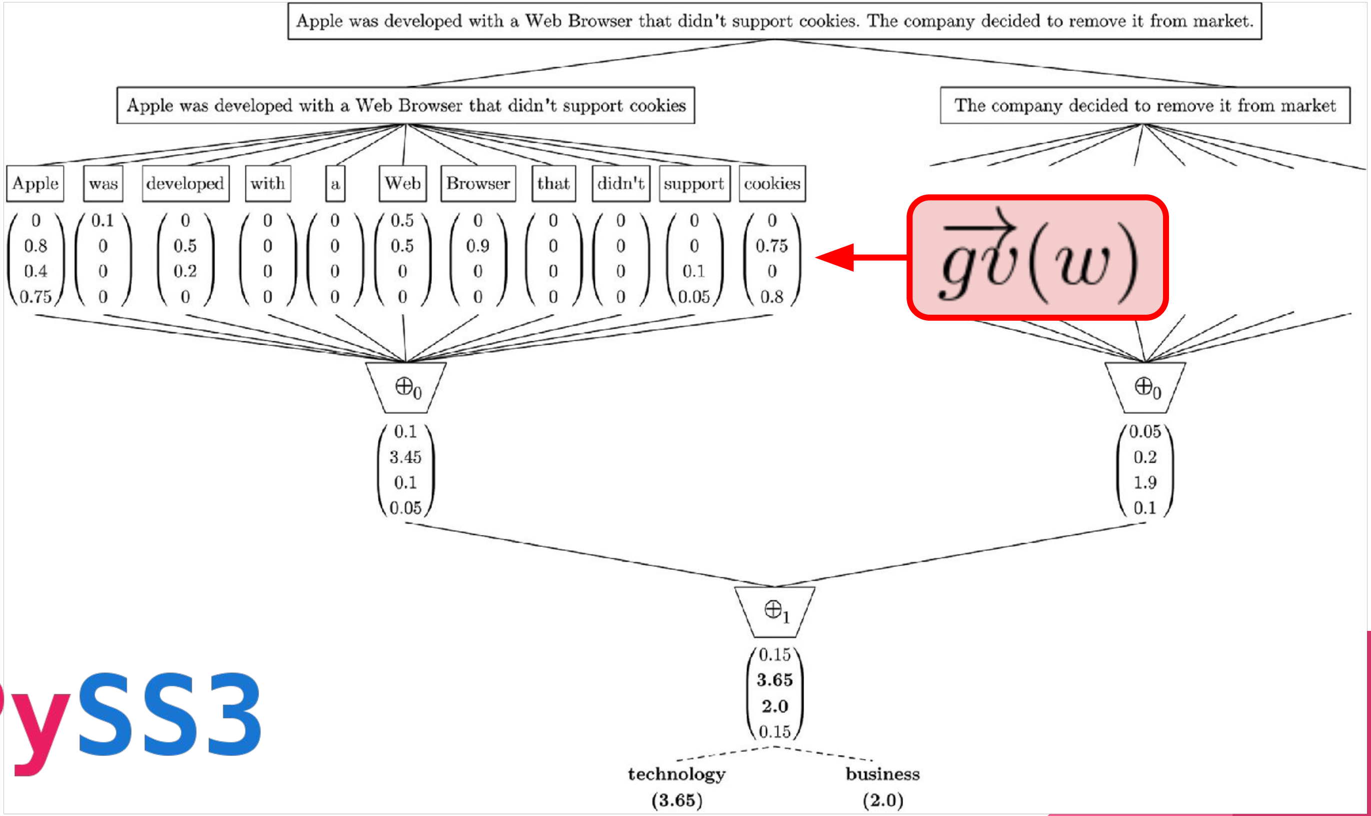


PySS3

https://github.com/sergioburdisso/pyss3

Burdisso et al. 2019

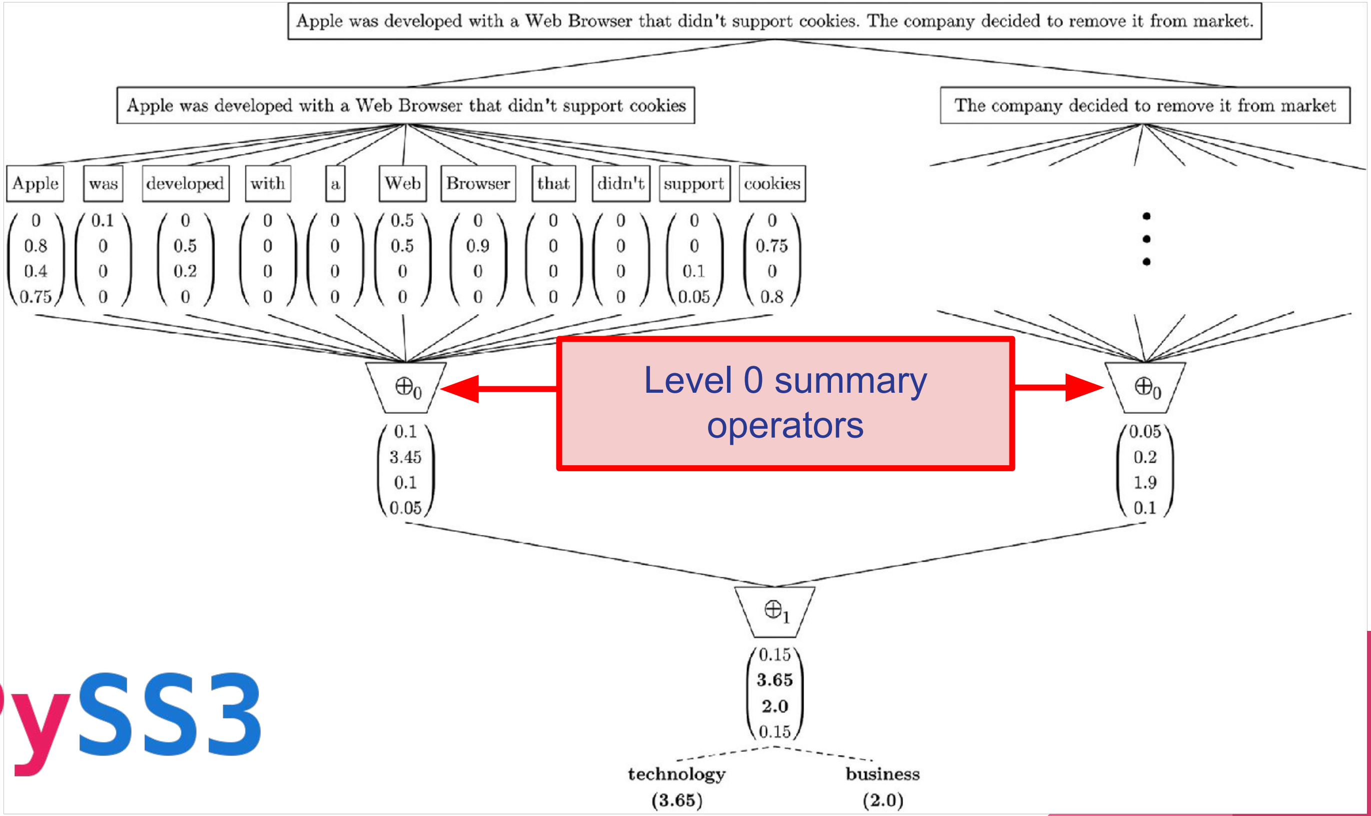
SS3



Apple was developed with a Web Browser that didn't support cookies. The company decided to remove it from market.
Apple was developed with a Web Browser that didn't support cookies
The company decided to remove it from market
Apple
was
developed
with
a
Web
Browser
that
didn't
support
cookies
$\vec{gv}(w)$
$\oplus_0$
$\oplus_0$
$\oplus_1$
technology (3.65)
business (2.0)

PySS3

SS3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was
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with
a
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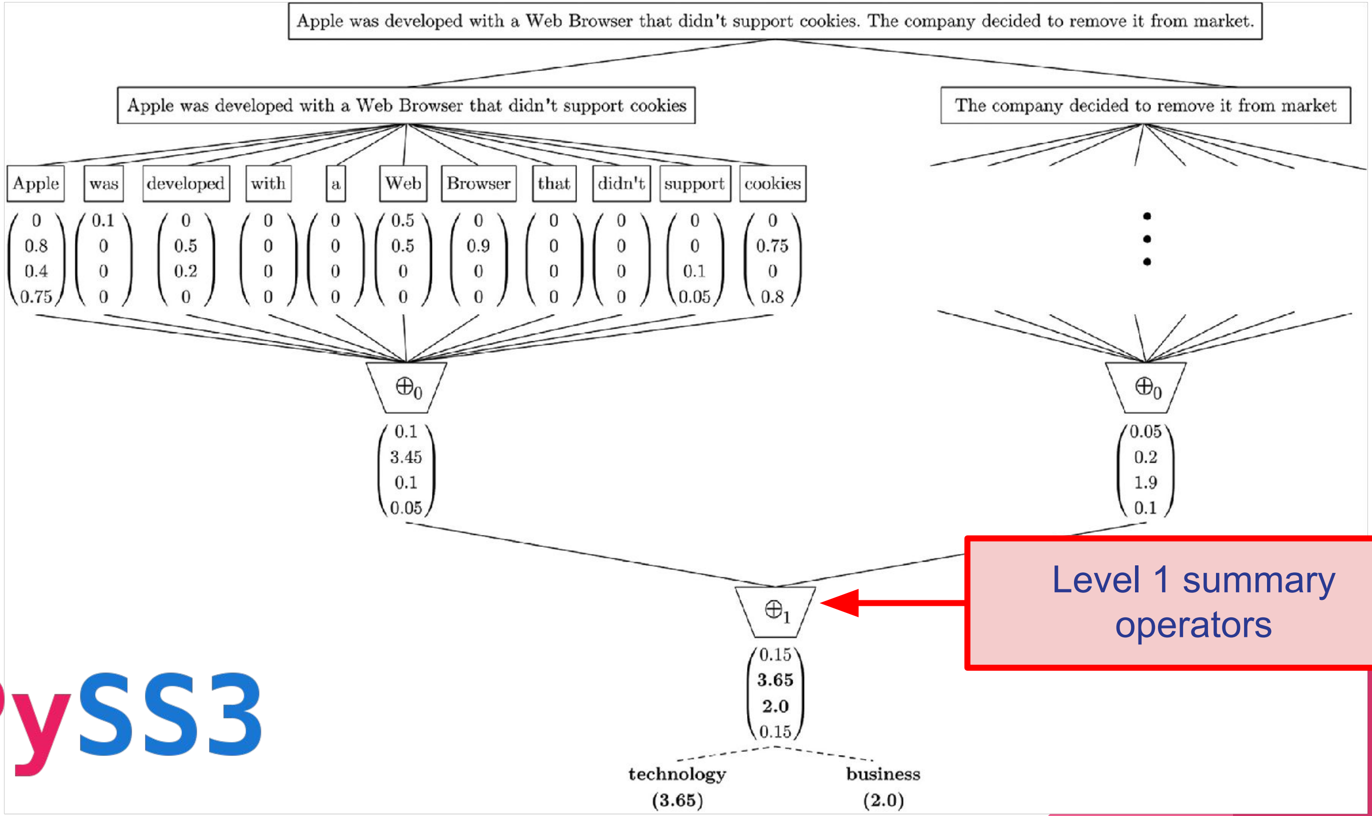
Browser
that
didn't
support
cookies
Level 0 summary operators
technology (3.65)
business (2.0)

PySS3

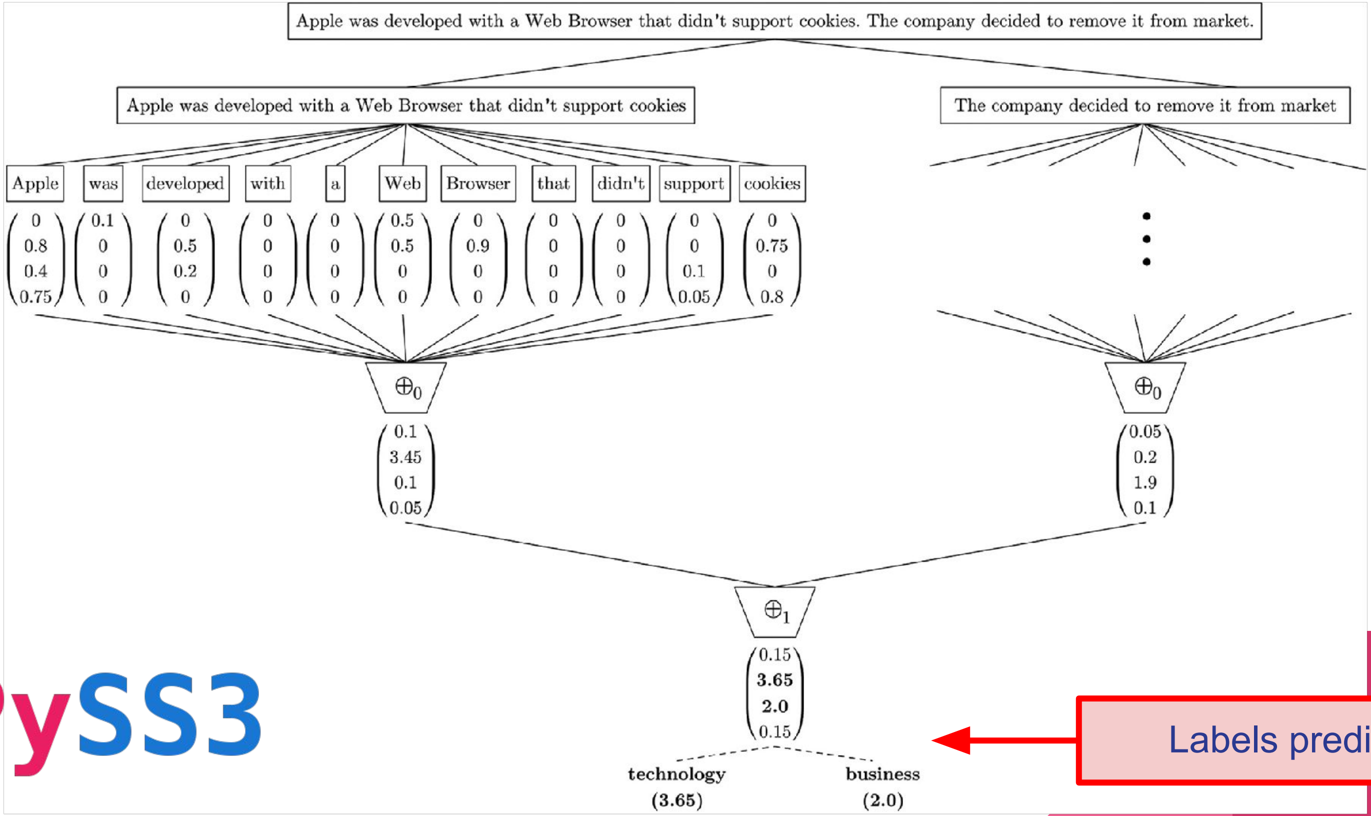
SS3



Level 1 summary operators

PySS3

SS3



Labels predicted

PySS3

https://github.com/sergioburdisso/pyss3

Burdisso et al. 2019

SS3

Early alert policy:

$$decision_u = \begin{cases} 1, & \text{if } score_u > \text{median}(scores) + \gamma \cdot \text{MAD}(scores) \\ 0, & \text{otherwise.} \end{cases}$$

SS3

Early alert policy:

$$decision_u = \begin{cases} 1, & \text{if } score_u > \text{median}(scores) + \gamma \cdot \text{MAD}(scores) \\ 0, & \text{otherwise.} \end{cases}$$

$\boxed{\text{Normalization (risk\_class\_score, non\_risk\_class\_score)}}$

SS3

Early alert policy:

$$decision_u = \begin{cases} 1, & \text{if } score_u > \text{median}(scores) + \gamma \cdot \text{MAD}(scores) \\ 0, & \text{otherwise.} \end{cases}$$

$$\boxed{scores = \{score_u | u \in \text{Users}\}}$$

SS3

Early alert policy:

$$decision_u = \begin{cases} 1, & \text{if } score_u > \text{median}(scores) + \gamma \cdot \underline{\text{MAD}}(scores) \\ 0, & \text{otherwise.} \end{cases}$$

Median Absolute Deviation

SS3

Early alert policy:

$$decision_u = \begin{cases} 1, & \text{if } score_u > \text{median}(scores) + \gamma \cdot \text{MAD}(scores) \\ 0, & \text{otherwise.} \end{cases}$$

Early alert policy hyper-parameter

SS3

Normalization of scores

- Since
  - the decision policy considers the model output for all the users,
  - the users have different posts number,
  - the model output is additive
- The final score of the users with a small number of posts affects the rest of the users.

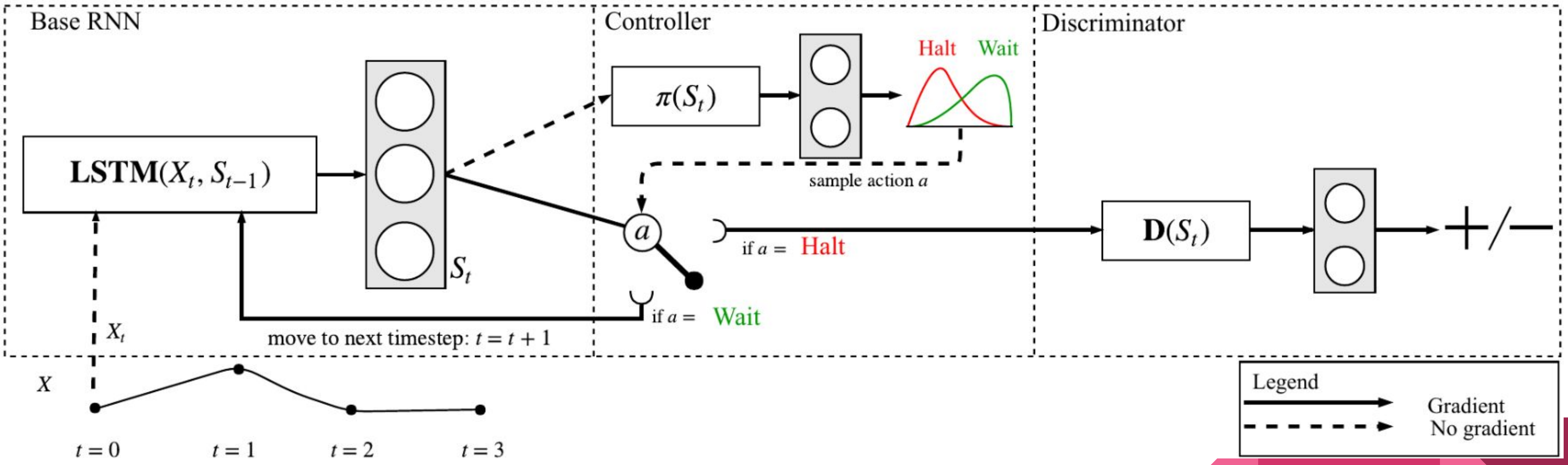
SS3

Normalization of scores:

- N1: $softmax(\frac{cv_{\text{positive}}}{\text{delay}}, \frac{cv_{\text{negative}}}{\text{delay}})$
- N2: $\frac{cv_{\text{positive}}}{cv_{\text{positive}} + cv_{\text{negative}}}$

EARLIEST

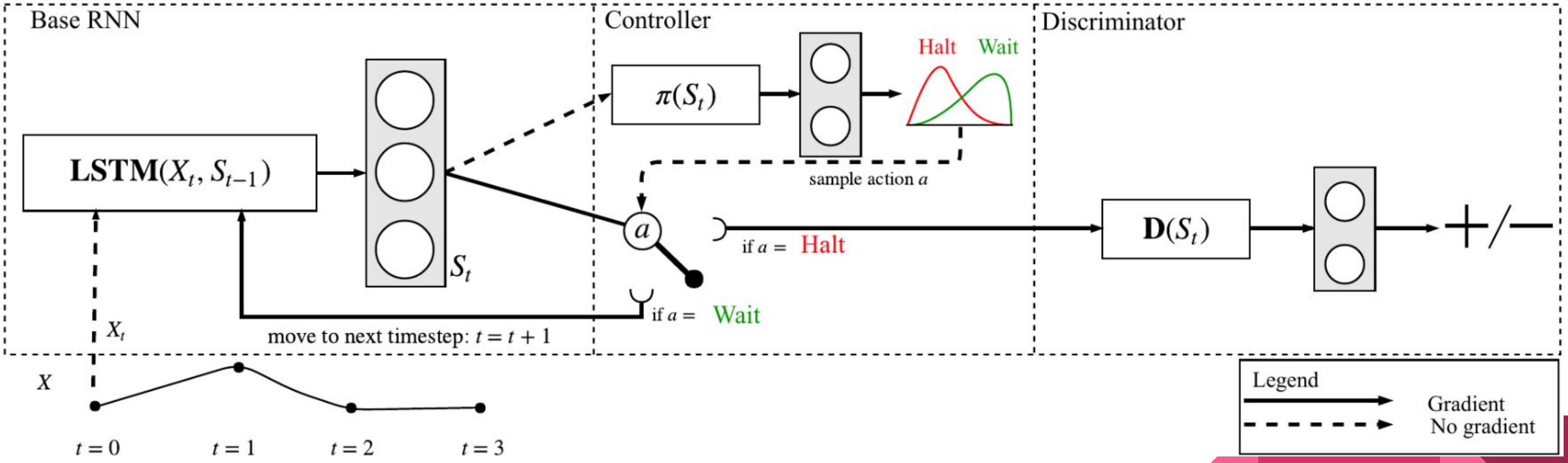
EARLIEST



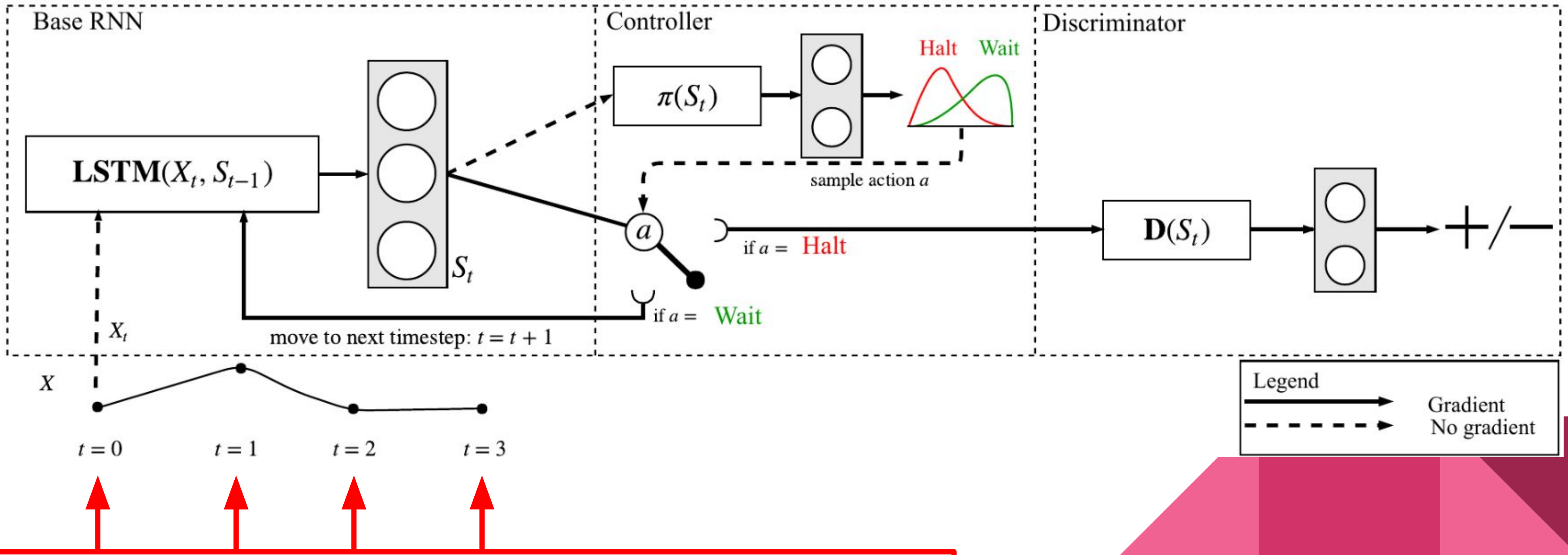
Base RNN
Controller
Discriminator
Halt
Wait
$\pi(S_t)$
LSTM(X_t, S_{t-1})
S_t
sample action a
a
$\mathbf{D}(S_t)$
+/—
if a = Halt
if a = Wait
X_t
move to next timestep: $t = t + 1$
X
$t = 0$
$t = 1$
$t = 2$
$t = 3$
Legend
Gradient
No gradient

EARLIEST

Early and Adaptive Recurrent Label ESTimator



EARLIEST

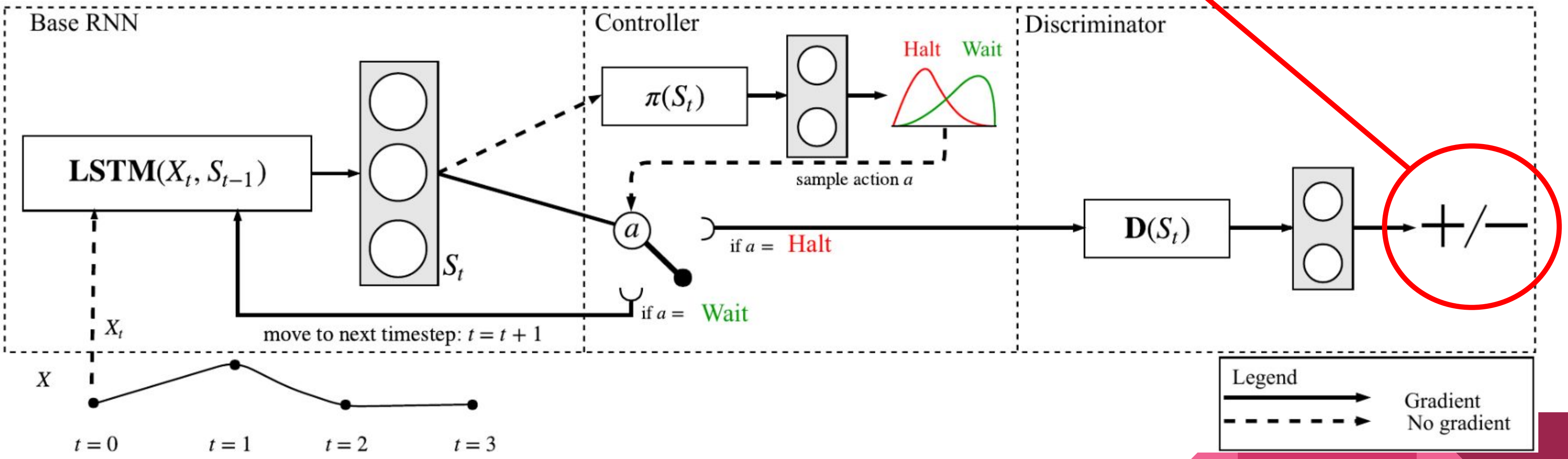


Sequence of input documents for a user (doc2vec)

Hartvigsen et al. 2019

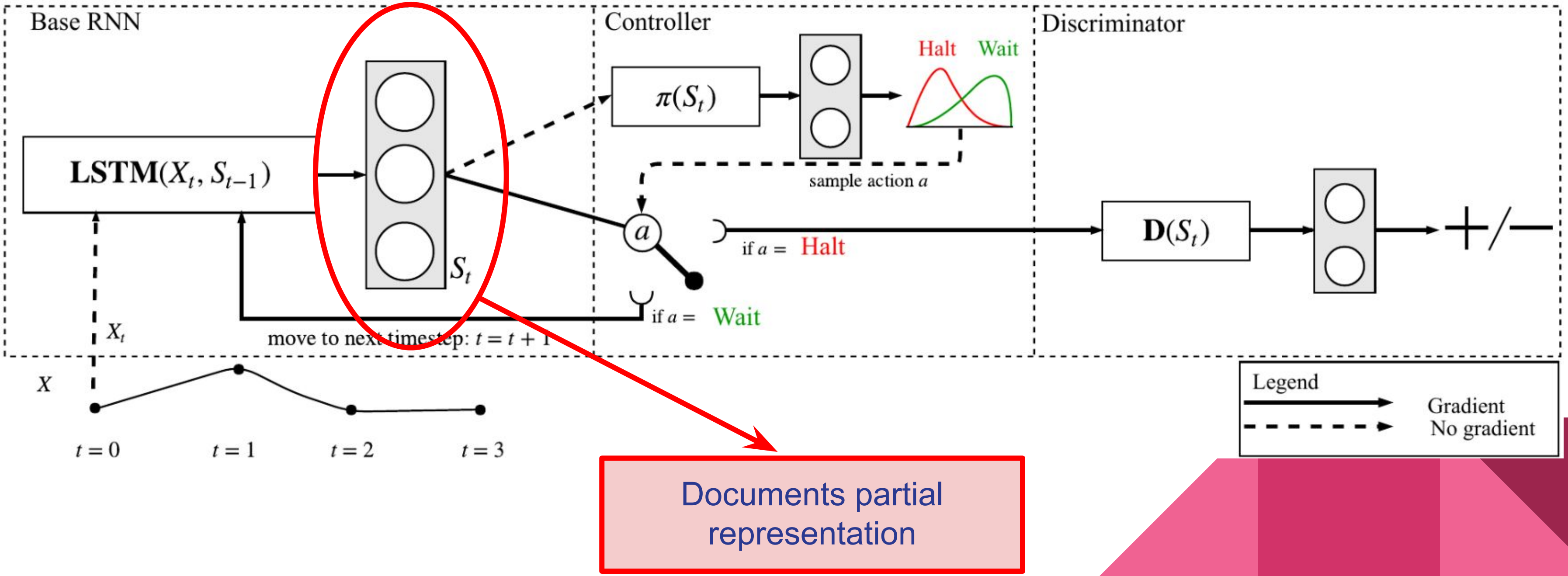
EARLIEST

Predicted user label
(risk or non-risk)



Hartvigsen et al. 2019

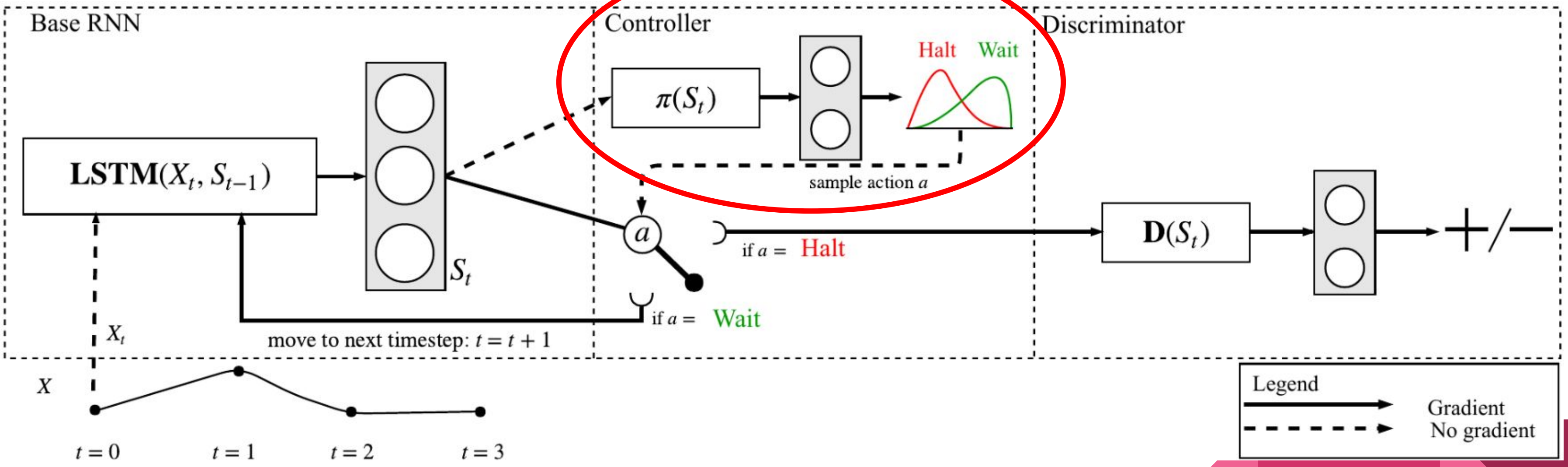
EARLIEST



Hartvigsen et al. 2019

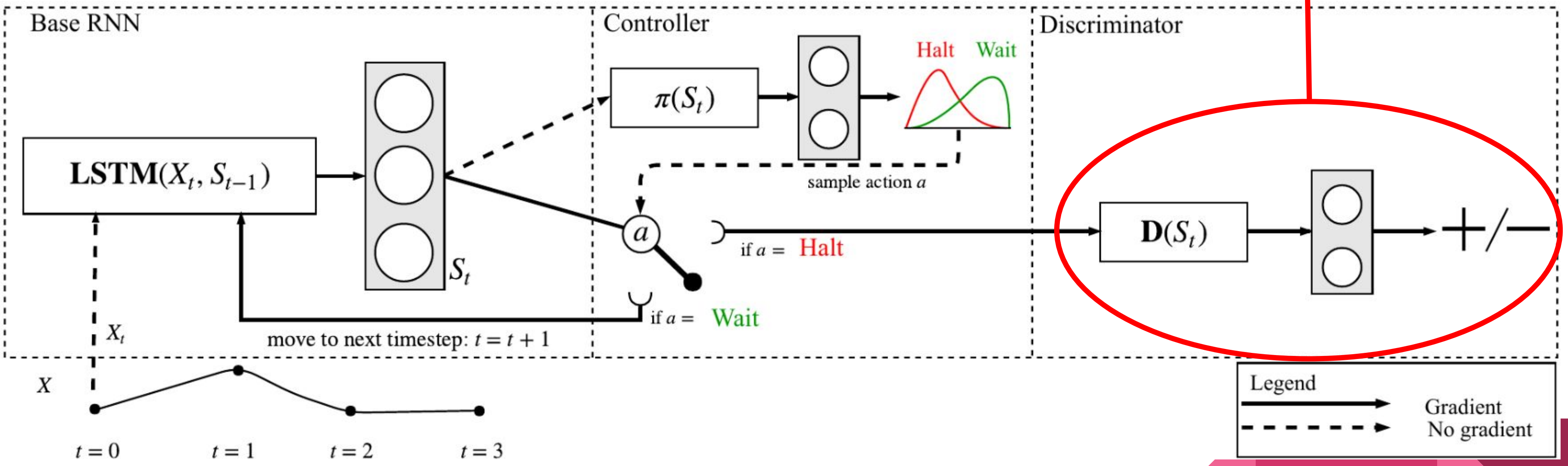
EARLIEST

Component in charge of deciding when to stop processing the input



EARLIEST

Component in charge of classifying the partial input



EARLIEST

The hyper-parameter λ penalizes the delay in the classification while training.

Runs and Results

Task 1: Early Detection of Signs of Pathological Gambling

Task 2: Early Detection of Depression

T1 - Early Detection of Pathological Gambling - Runs

- UNSL#0 (EarlyModel):
  - Representation ⟶ bag of words (unigrams of words with tf-idf)
  - Model ⟶ logistic regression
  - Decision policy ⟶ SSC (threshold = 0.7 and min. num. of post = 10)
- UNSL#1 (EarlyModel):
  - Representation ⟶ bag of words (4-grams of characters with tf-idf)
  - Model ⟶ SVM
  - Decision policy ⟶ SSC (threshold = 0.7 and min. num. of post = 10)
- UNSL#2 (EarlyModel):
  - Representation ⟶ tokenizer
  - Model ⟶ BERT
  - Decision policy ⟶ HSC (threshold = 0.7, min. num. of post = 10 and 10 prev. preds)

T1 - Early Detection of Pathological Gambling - Runs

- UNSL#3 (SS3):
  - Representation ⟶ raw text
  - Model ⟶ SS3
  - Normalization ⟶ N1
  - Decision policy ⟶ γ = 2.5
- UNSL#4 (EARLIEST):
  - Representation ⟶ doc2vec
  - Model ⟶ LSTM
  - Decision policy ⟶ λ = 0.0001

T1 - Early Detection of Pathological Gambling - Results

Team	Run	P	R	$F1$	$ERDE_5$	$ERDE_{50}$	$latency_{TP}$	$speed$	$latency\text{-}weighted\ F1$
UNED-NLP	4	0.809	0.938	**0.869**	0.020	**0.008**	3.0	0.992	**0.862**
SINAI	0	0.425	0.765	0.546	**0.015**	0.011	**1.0**	**1.000**	0.546
SINAI	1	0.575	0.802	0.670	**0.015**	0.009	**1.0**	**1.000**	0.670
BLUE	0	0.260	0.975	0.410	**0.015**	0.009	**1.0**	**1.000**	0.410
UNSL (EarlyModel)	0	0.401	0.951	0.564	0.041	**0.008**	11.0	0.961	0.542
UNSL (EarlyModel)	1	0.461	0.938	0.618	0.041	**0.008**	11.0	0.961	0.594
UNSL (EarlyModel)	2	0.398	0.914	0.554	0.041	**0.008**	12.0	0.957	0.531
UNSL (SS3)	3	0.365	0.864	0.513	0.017	0.009	3.0	0.992	0.509
UNSL (EARLIEST)	4	0.052	0.988	0.100	0.051	0.030	5.0	0.984	0.098

T1 - Early Detection of Pathological Gambling - Results

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T2 - Early Detection of Depression - Runs

- UNSL#0 (EarlyModel):
  - Representation $\longrightarrow$ latent semantic analysis
  - Model $\longrightarrow$ logistic regression
  - Decision policy $\longrightarrow$ LDTSC
- UNSL#1 (EarlyModel):
  - Representation $\longrightarrow$ bag of words (3-grams of characters with tf-idf)
  - Model $\longrightarrow$ SVM
  - Decision policy $\longrightarrow$ SSC (threshold = 0.7 and min. num. of post = 10)
- UNSL#2 (SS3):
  - Representation $\longrightarrow$ raw text
  - Model $\longrightarrow$ SS3
  - Normalization $\longrightarrow$ N1
  - Decision policy $\longrightarrow$ γ = 2.5

T2 - Early Detection of Depression - Runs

- UNSL#3 (SS3):
  - Representation → raw text
  - Model → SS3
  - Normalization → N2
  - Decision policy → γ = 2
- UNSL#4 (EARLIEST):
  - Representation → doc2vec
  - Model → LSTM
  - Decision policy → λ = 0.0001

T2 - Early Detection of Self-Harm - Results

Team	Run	P	R	$F1$	$ERDE_5$	$ERDE_{50}$	$latencyTP$	$speed$	$latency\text{-}weighted\ F1$
LauSAn	4	0.201	0.724	0.315	**0.039**	0.033	**1.0**	**1.000**	0.315
NLPGroup-IISERB	0	0.682	0.745	**0.712**	0.055	0.032	9.0	0.969	**0.690**
SCIR2	3	0.316	0.847	0.460	0.079	**0.026**	44.0	0.834	0.383
UNSL (EarlyModel)	0	0.161	0.918	0.274	0.079	0.042	14.5	0.947	0.260
UNSL (EarlyModel)	1	0.310	0.786	0.445	0.078	0.037	12.0	0.957	0.426
UNSL (SS3)	2	0.400	0.755	0.523	0.045	**0.026**	3.0	0.992	0.519
UNSL (SS3)	3	0.144	0.929	0.249	0.055	0.035	3.0	0.992	0.247
UNSL (EARLIEST)	4	0.080	0.918	0.146	0.099	0.074	5.0	0.984	0.144

T2 - Early Detection of Self-Harm - Results

Team	Run	P	R	$F1$	$ERDE_5$	$ERDE_{50}$	$latencyTP$	$speed$	$latency\text{-}weighted\ F1$
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Thank you for your attention.
Any questions?

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References

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- Hartvigsen, T., Sen, C., Kong, X., & Rundensteiner, E. (2019, July). Adaptive-halting policy network for early classification. In Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining (pp. 101-110).

Corpus generation procedure

- Based on posts and comments from Reddit (https://www.reddit.com/).
- Positive cases were obtained from particular subreddits
  - T1: https://www.reddit.com/r/problemgambling/
  - T2: https://www.reddit.com/r/depression
- Negative cases were obtained from general subreddits: sports, jokes, gaming, politics, news, y LifeProTips.
- All users with less than 31 posts or comments, or with an average number of words per post less than 15, were discarded.

T1 - eRisk corpus

- Based on posts and comments from Reddit (https://www.reddit.com/).
- A corpus was supplied which was used for validation.

Corpus	#users			#posts	#posts per user			#words per post		
	Total	Pos	Neg		Med	Min	Max	Med	Min	Max
T1_test	2,079	81	1,998	1,177,590	297	3	2,001	11	0	6,728
T1_valid	2,348	164	2,184	1,130,799	244	10	2,001	11	1	8,241
T1_redd_train	1,746	286	1,460	158,924	51	31	1,188	20	1	7,479
T1_redd_valid	1,746	286	1,460	161,204	53	31	1,337	20	1	3,234

T2 - eRisk corpus

- Based on posts and comments from Reddit (https://www.reddit.com/).
- A training and validation corpus were provided.

Corpus	#users			#posts	#posts per user			#words per post		
	Total	Pos	Neg		Med	Min	Max	Med	Min	Max
T2_test	1,400	98	1,302	898,326	457.0	6	2,000	12	0	8,009
T2_train	887	135	752	531,394	321.0	10	2,000	13	1	7,450
T2_valid	820	79	741	545,188	411.5	10	2,000	13	1	7,280
T2_redd_train	1,056	499	557	142,059	66.0	31	2,282	21	1	6,792
T2_redd_valid	1,057	500	557	130,534	61.0	31	2,220	20	1	6,629