Distributed Classification of Text Streams: Limitations, Challenges, and Solutions

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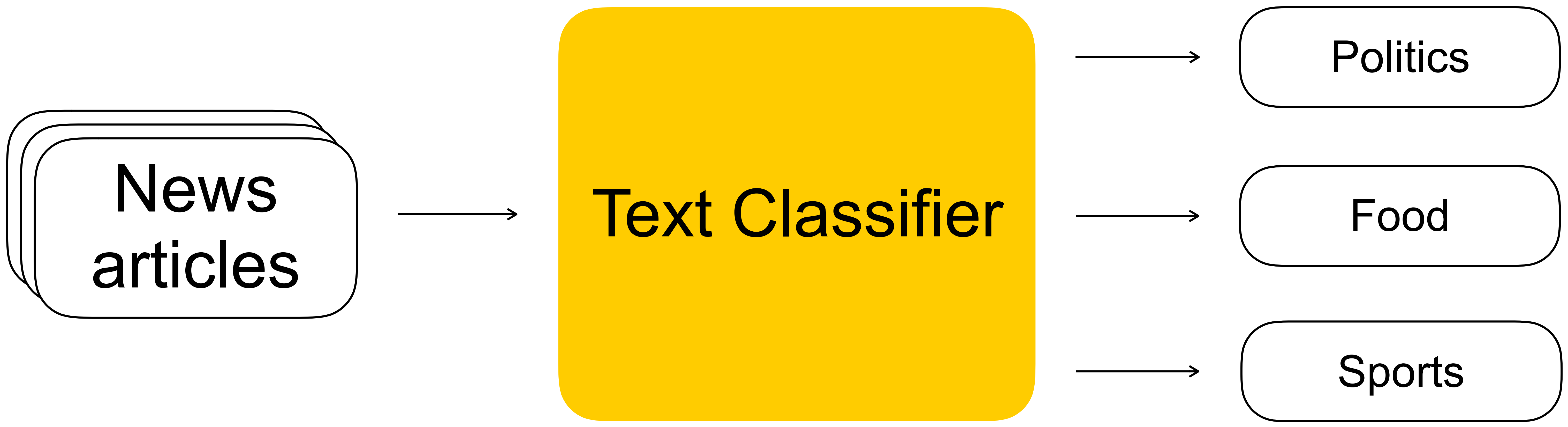
Classification of text streams: an example

News articles classification

- Multi-classification problem
- Automated news aggregation
- Event-based decisions



Classification of text streams: requirements

Production-ready solution

- Scalability
- Low latency
- Reproducibility
- Fault tolerance

Existing tools: python libraries, batch systems

```
>>> from sklearn.linear_model import SGDClassifier
>>> text_clf = Pipeline([
...     ('vect', CountVectorizer()),
...     ('tfidf', TfidfTransformer()),
...     ('clf', SGDClassifier(loss='hinge', penalty='l2',
...                           alpha=1e-3, random_state=42,
...                           max_iter=5, tol=None)),
... ])
```

```
>>> text_clf.fit(twenty_train.data, twenty_train.target)
Pipeline(...)
>>> predicted = text_clf.predict(docs_test)
>>> np.mean(predicted == twenty_test.target)
0.9101...
```

hadoop

MAHOUT

Not scalable

High latency

Text classifier on top of distributed stream processing

Existing tools: distributed stream processing

Apache SAMOA
Scalable Advanced Massive Online Analysis

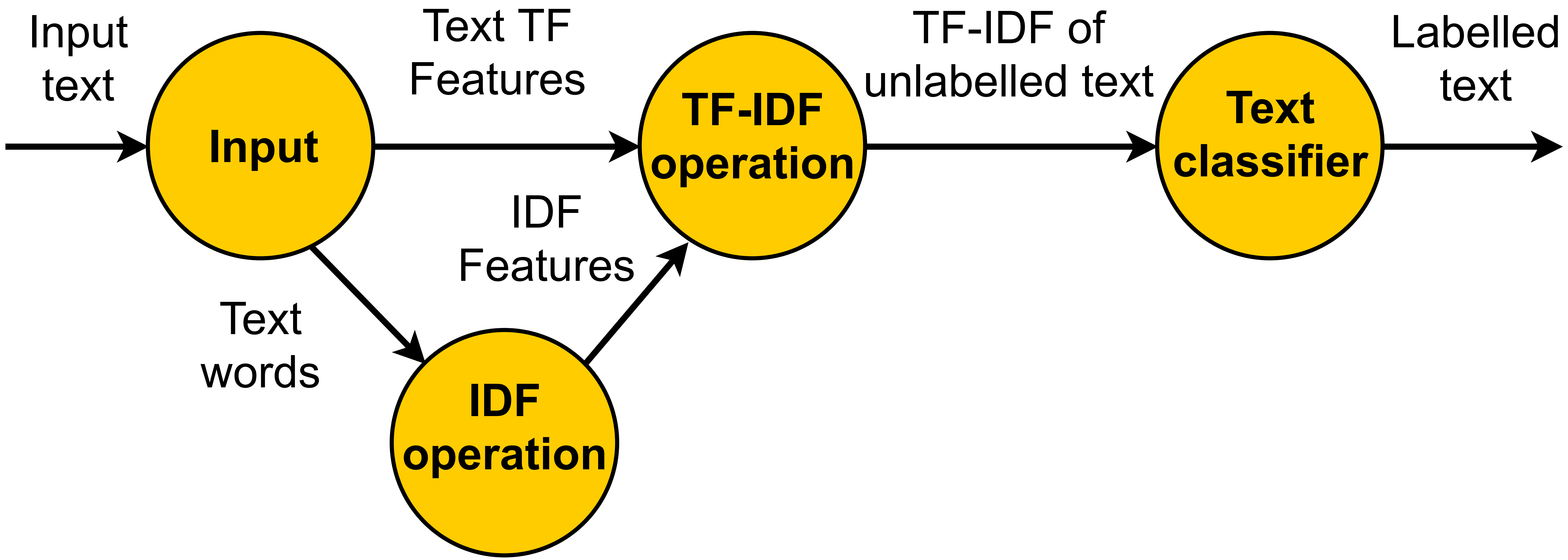
Spark Streaming

APACHE STORM™

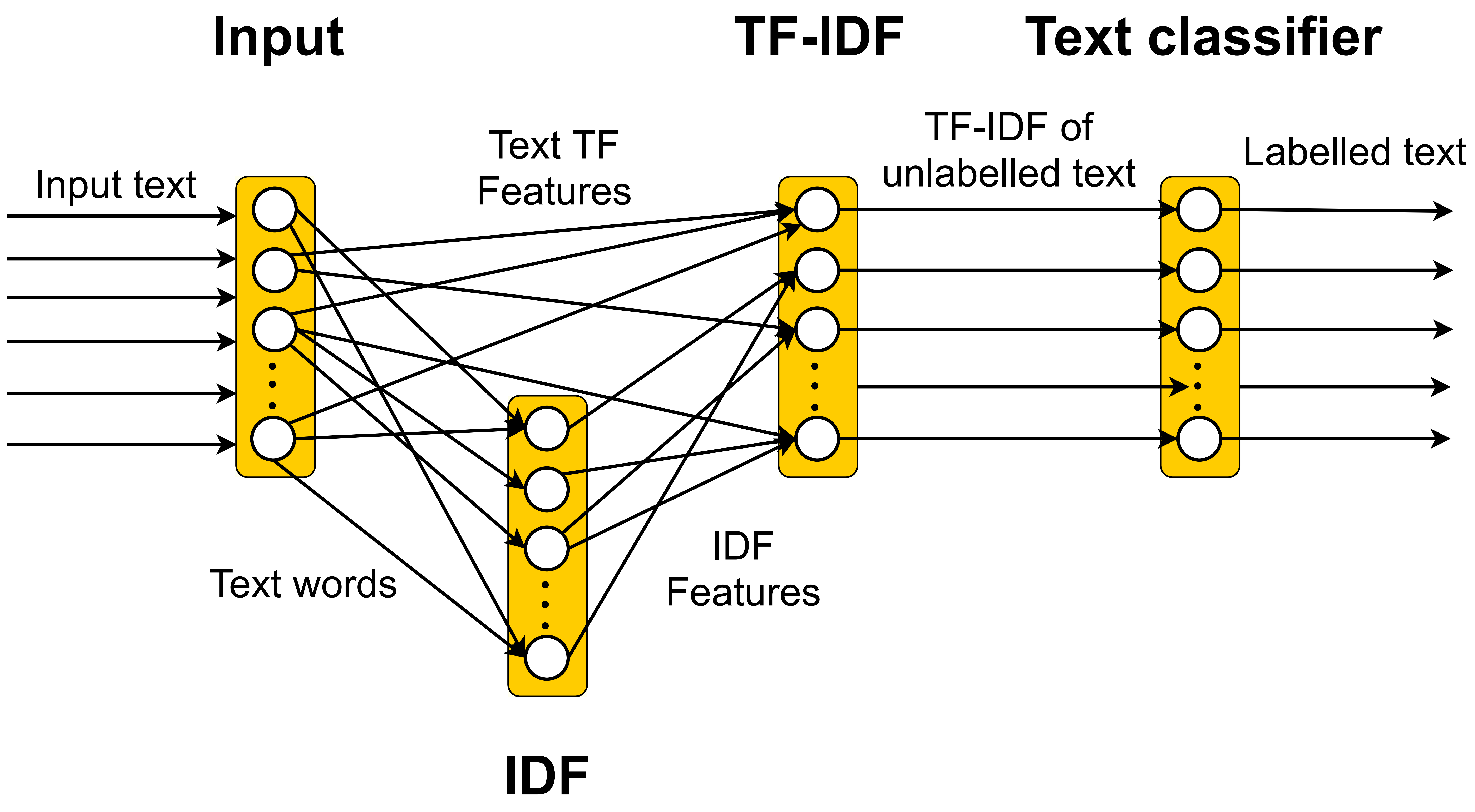
MLlib
The Machine Learning Library

Stream processing: building logical graph

- Bag-of-words model
- TF-IDF features



Stream processing: physical graph



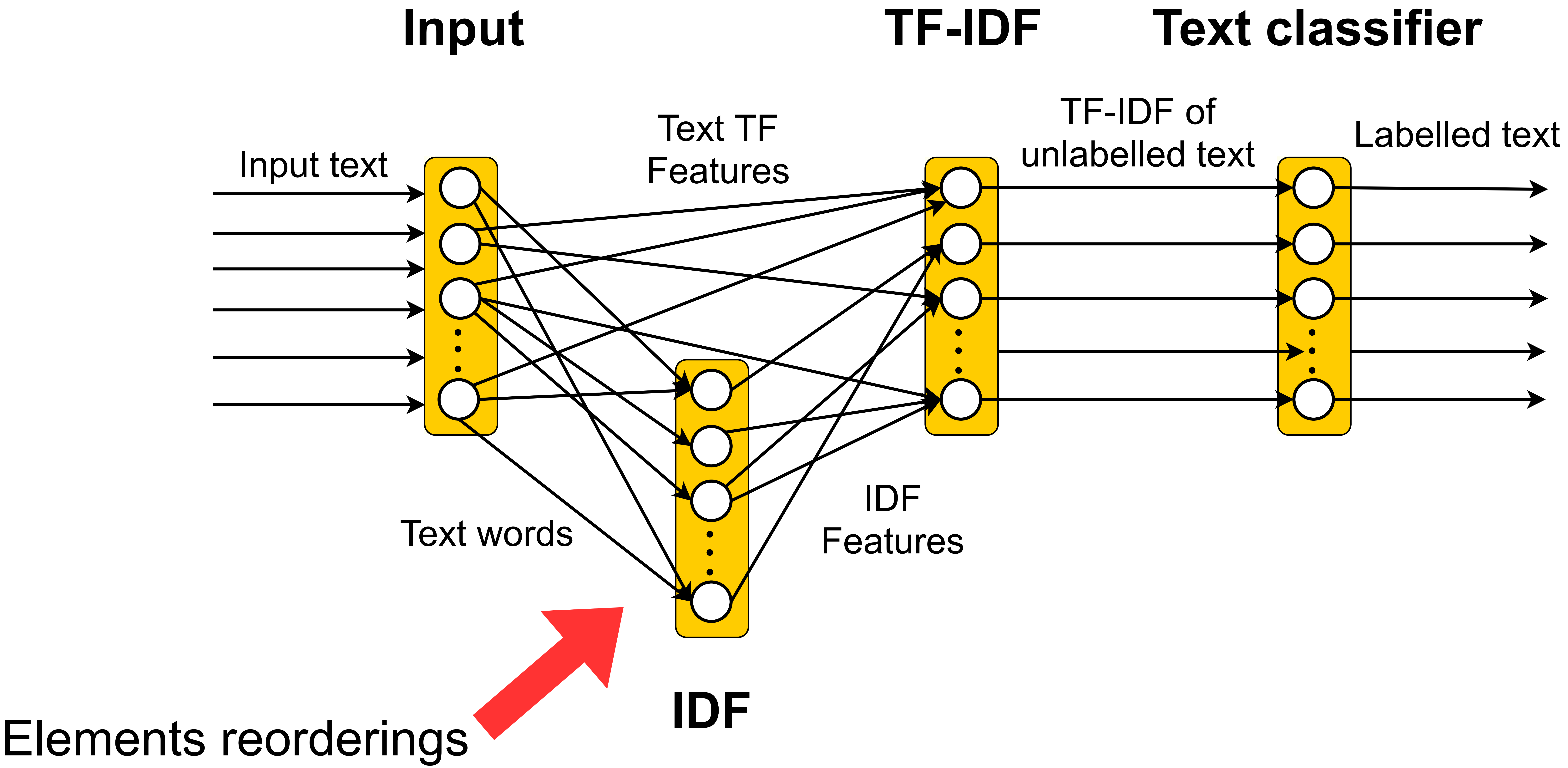
Text classification on top of distributed stream processing system

Perfect solution? Let's try!

- Apache Flink
- Multinomial logistic regression (less than 1% regret in comparison with SVM)
- lenta.ru dataset: 200.000 articles, 90 classes
- Amazon EC2 small instances

Reproducibility

Pitfall #1: races in dataflow



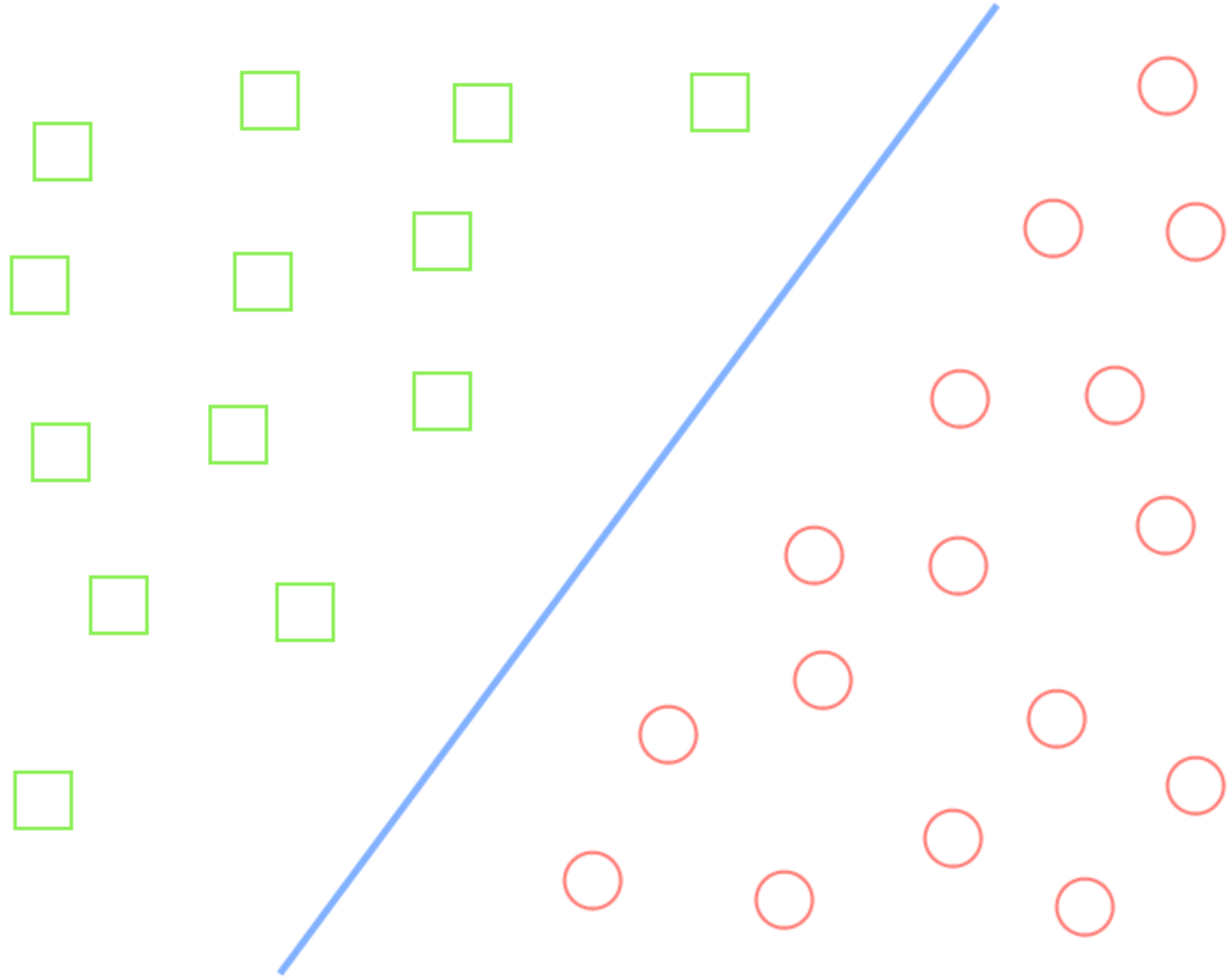
Races in dataflow: experiments

- 10 independent launches
- Results of individual points can be irreproducible

Cluster size	% of varied labels(mean±std)	Accuracy % (77.3)
2	0.9 ± 0.2	77.3 ± 0.2
4	1.7 ± 0.4	77.3 ± 0.2
8	1.9 ± 0.5	77.3 ± 0.2

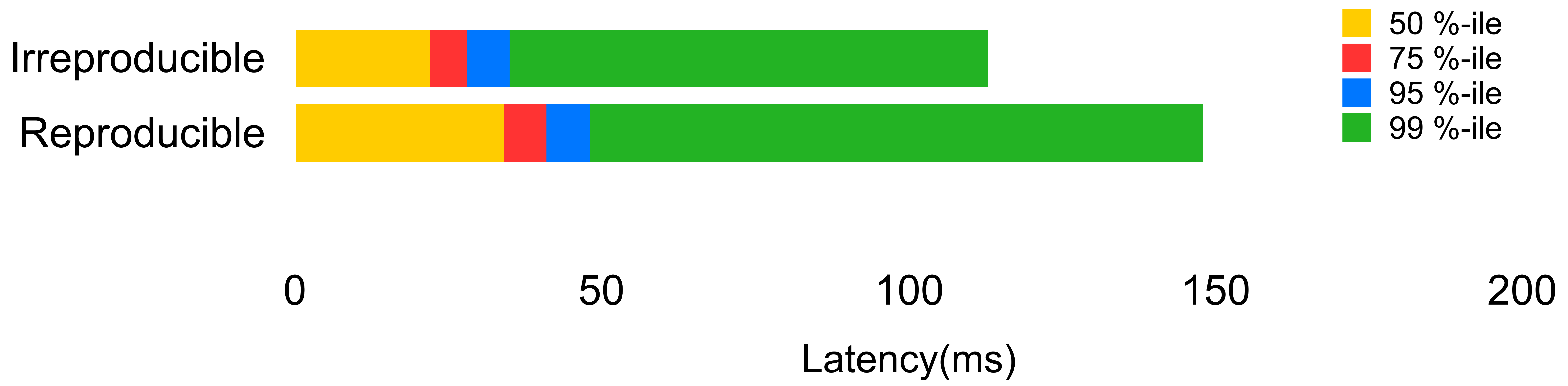
Races in dataflow: experiment explanation

- Differently labeled points are near discriminative surface
- Dependency from classifier accuracy requires further investigation



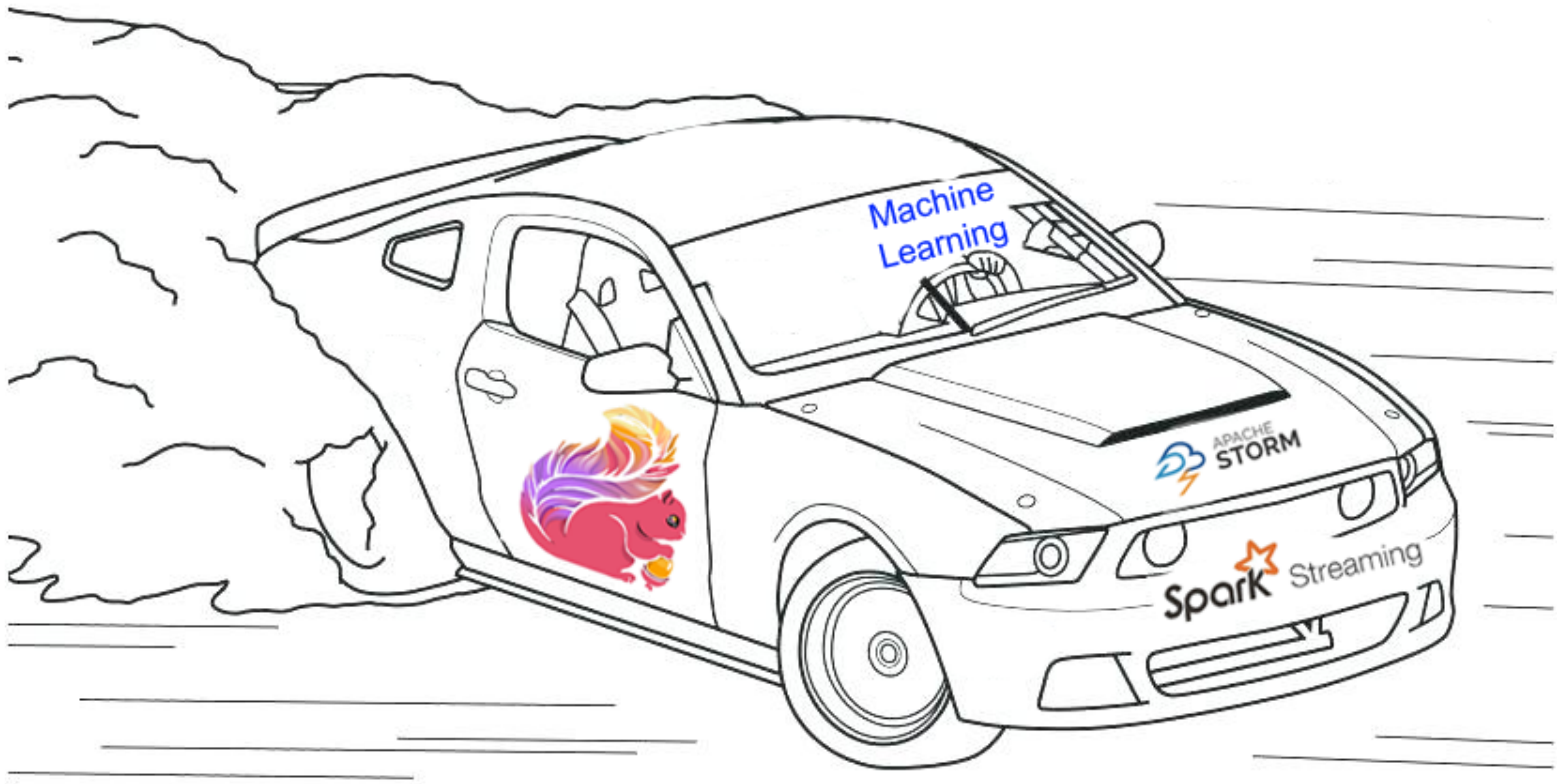
Races in dataflow: straightforward resolution

- Set order on elements
- Buffer until punctuation (watermark) arrives
- Sort according to the order



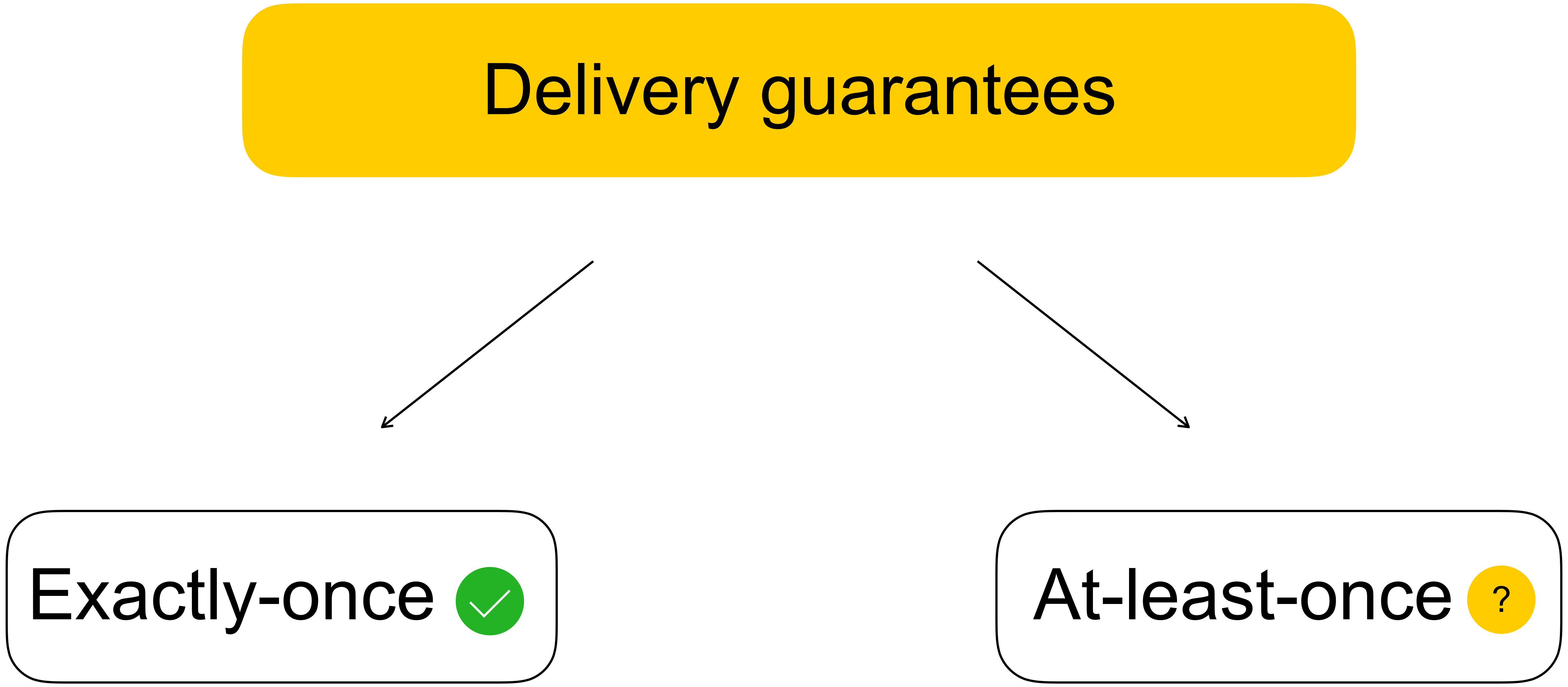
Races in dataflow: overview

- Can affect the result of individual documents, but not accuracy
- Should be considered if reproducibility in terms of individual elements matters
- Straightforward solution has slight latency overhead



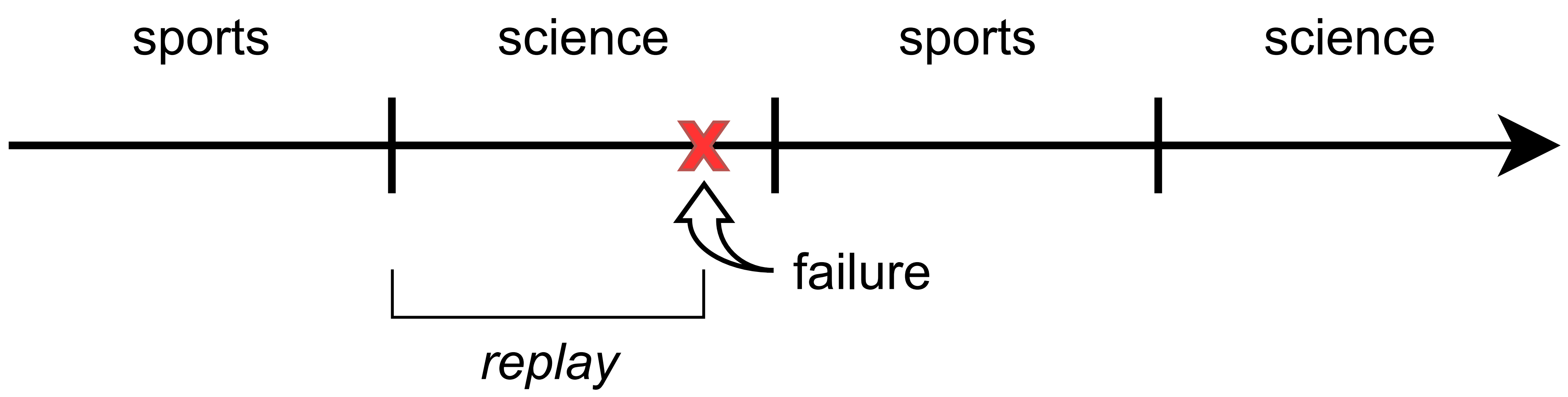
Fault tolerance

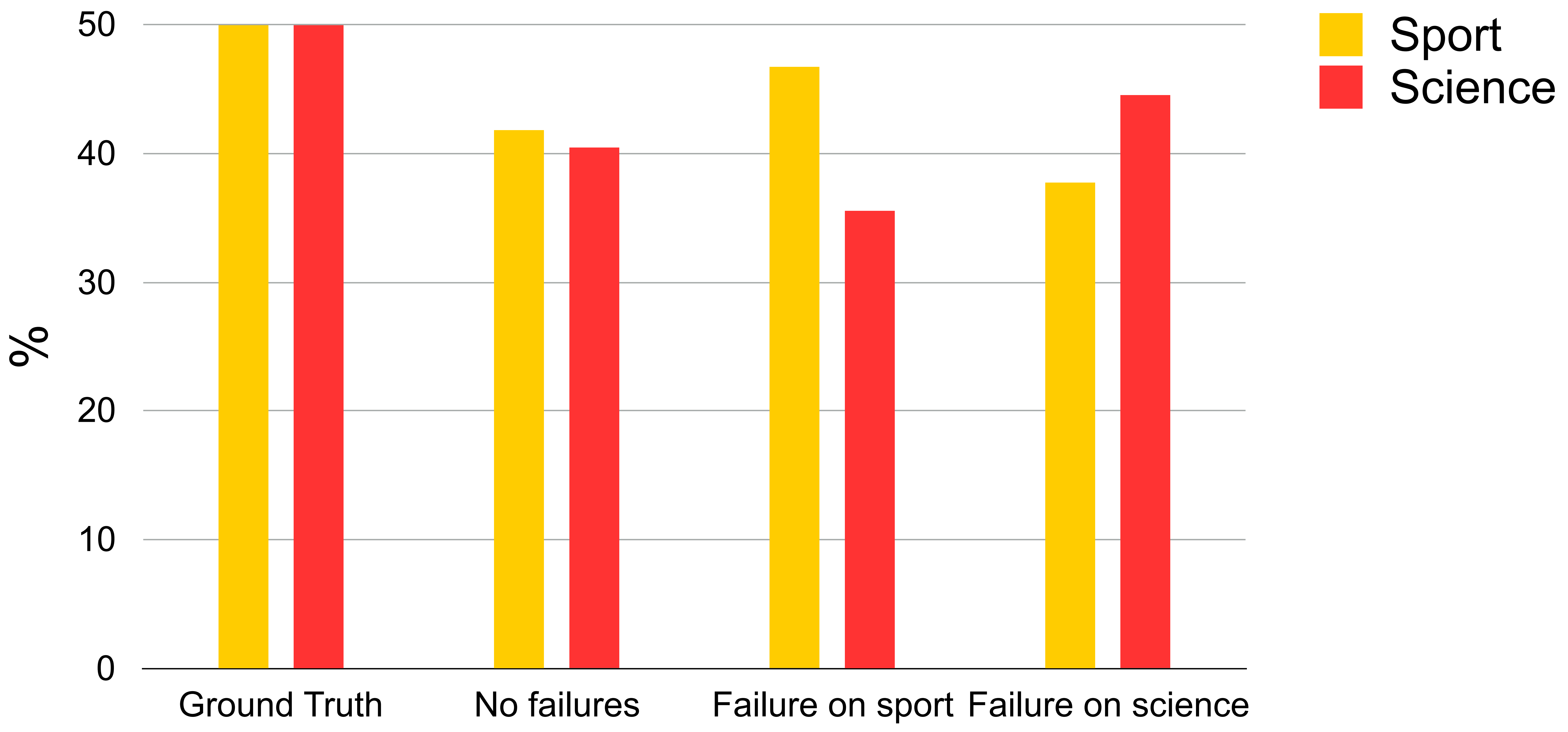
Pitfall #2: the choice of delivery guarantee



At-least-once: biased distribution

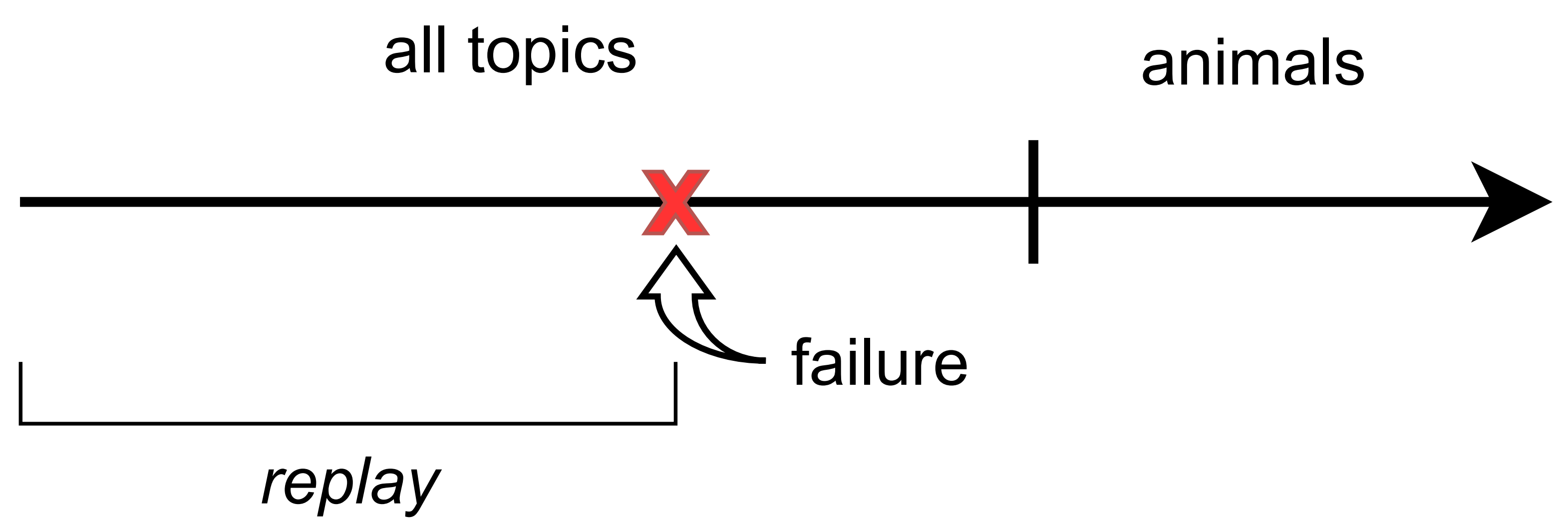
- 4000 articles (window)
- Sport and science topics
- 2 Amazon EC2 small instances

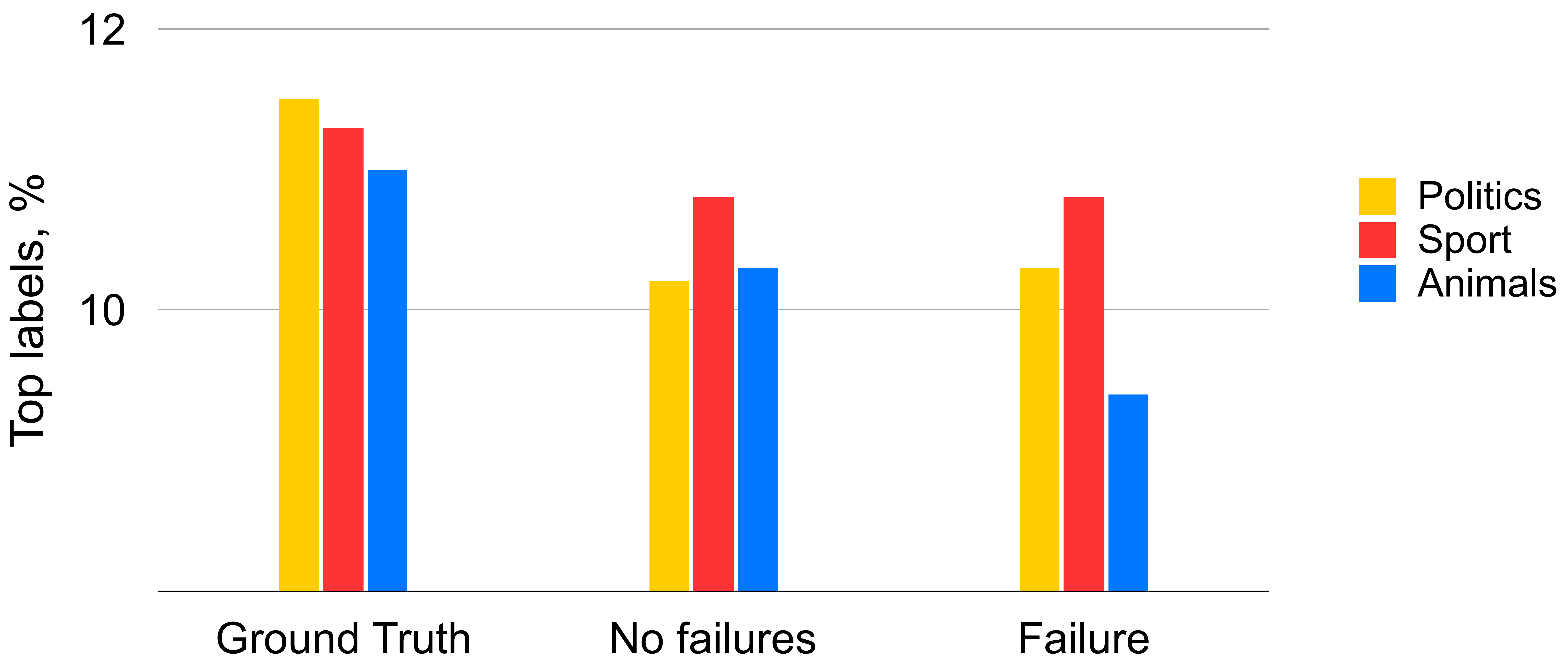




At-least-once: biased threshold

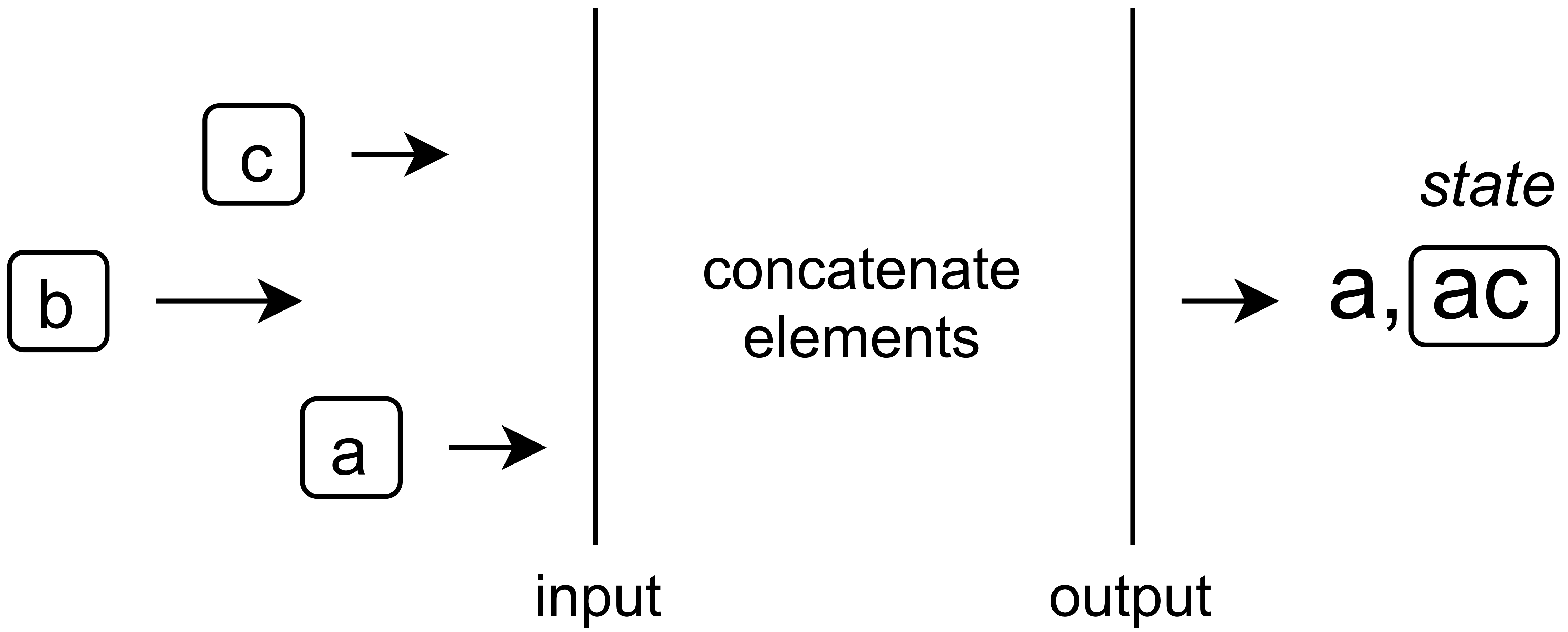
- 5000 articles (window)
- Looking for “popular” topics
- 2 Amazon EC2 small instances





Overhead on exactly once: causes

- Latency depends on snapshotting period in non-deterministic systems



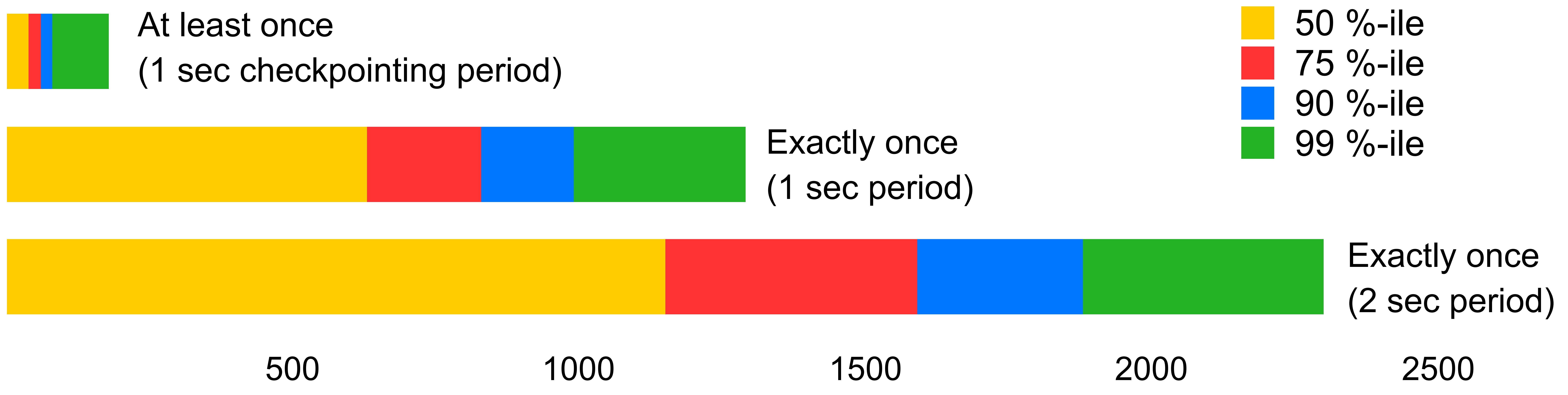
failure ⟶ restore state

restored state: $\boxed{\text{ca}}$

output: a, ac, bca

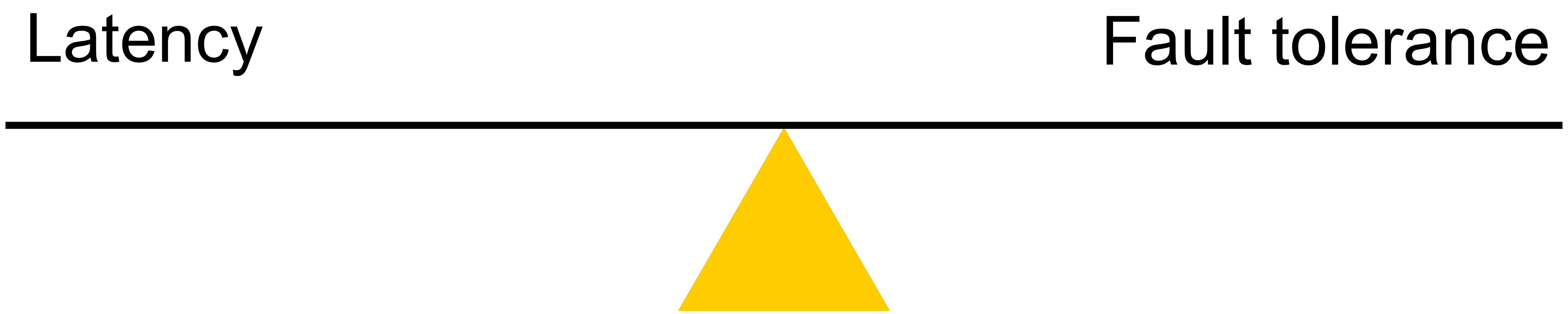
Overhead on exactly once: experiment

- Apache Flink
- 1 and 2 seconds period between snapshots
- 2 Amazon EC2 small instances



Fault tolerance: overview

- Failures within at-least-once guarantee can significantly influence results
- Overhead on exactly-once is high in state-of-the-art stream processing systems



Promising directions

System	Exactly-once	Determinism	Latency
Storm	–	–	low (< 500 ms)
Heron	–	–	low
Samza	–	–	low
Apache Spark	+	+	high
Flink	+	–	high*
MillWheel	+	+	NA
FlameStream	+	+	low

* - with enabled exactly-once

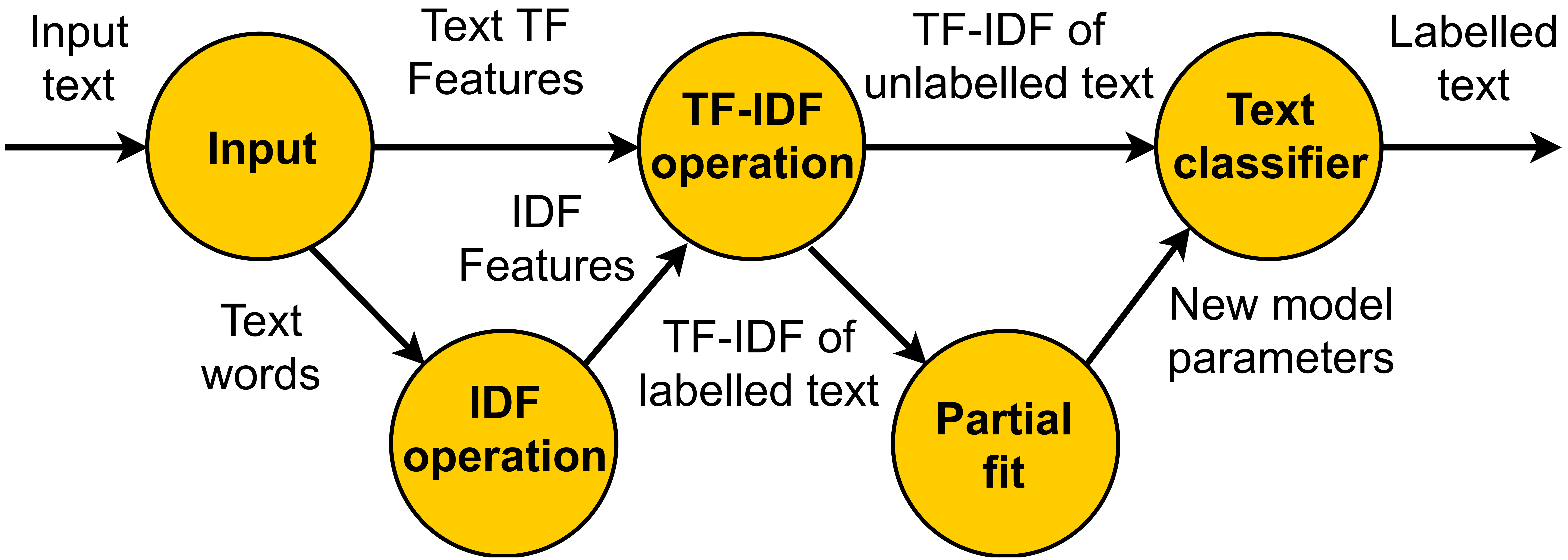
› Zacheilas, N., Kalogeraki, V., Nikolakopoulos, Y., Gulisano, V., Papatriantafilou, M., & Tsigas, P. (2017, June). Maximizing determinism in stream processing under latency constraints. In Proceedings of the 11th ACM International Conference on Distributed and Event-based Systems (pp. 112-123). ACM.

› Kuralenok, I. E., Trofimov, A., Marshalkin, N., & Novikov, B. (2018, September). Deterministic Model for Distributed Speculative Stream Processing. In European Conference on Advances in Databases and Information Systems (pp. 233-246). Springer, Cham.

On-the-fly model updates

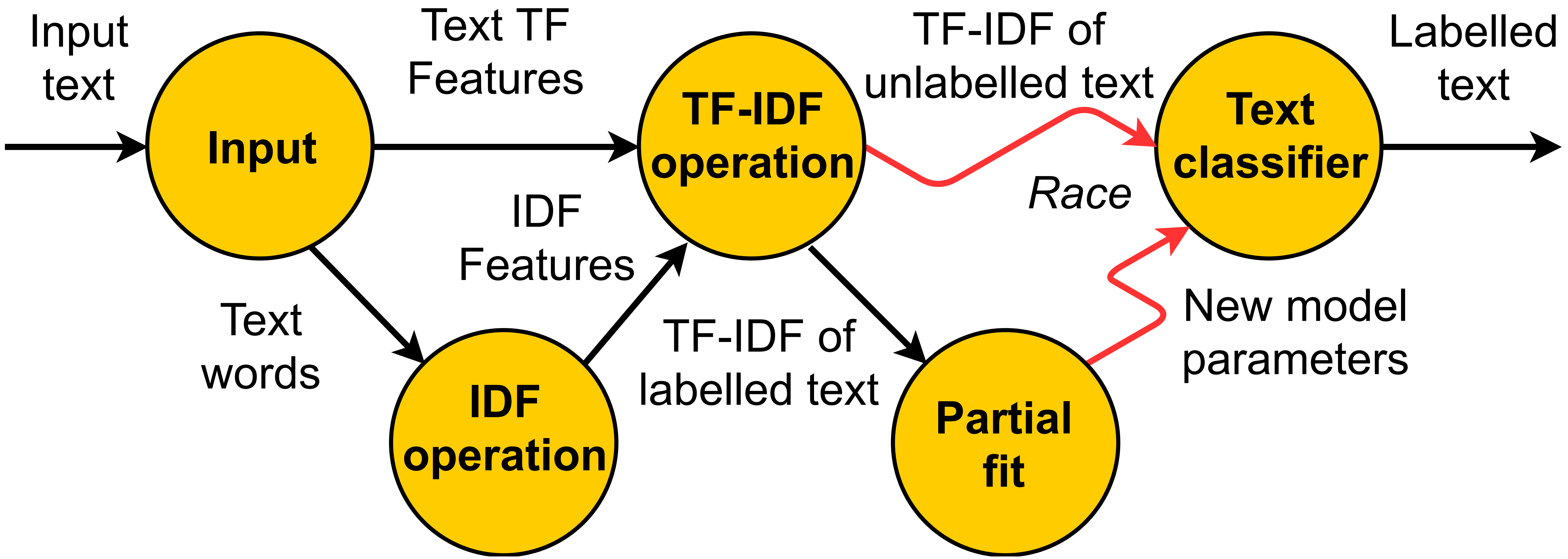
Pitfall #3: on-the-fly model updates

- Data is rapidly changing
- Two types of elements: pre-labeled and raw
- Raw elements should update ML model



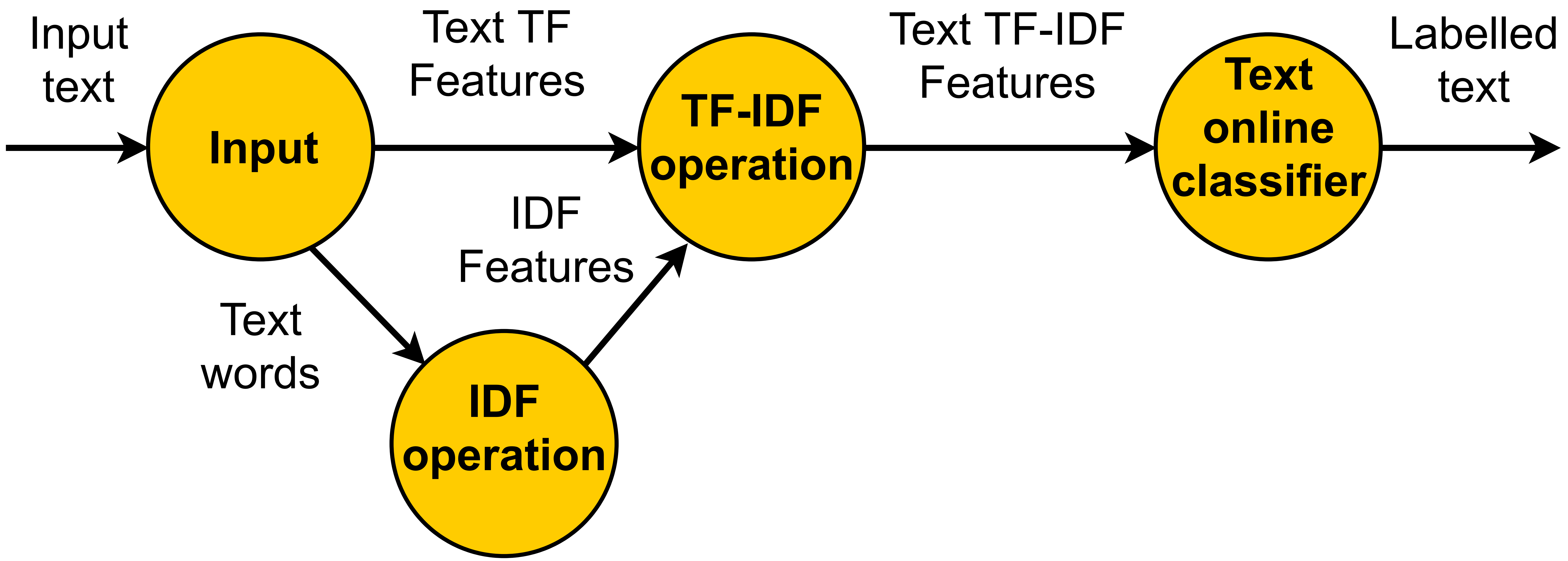
On-the-fly model updates: reproducibility

- Training process may be time-consuming
- Consecutive training and prediction -> latency spikes
- Online learning!



On-the-fly model updates: future work

- Straightforward solution leads to latency spikes or irreproducibile results
- Only online learning algorithms are suitable



Conclusion

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- Moving to distributed streaming environment is complex
- Migration of even simple pipeline can be a difficult problem
- There are no automatic tools for migration or for finding issues
- There are several approaches which can potentially fix the problems: deterministic stream processing and online learning algorithms