Optimizing Machine Learning Workloads in Collaborative Environments

Behrouz Derakhshan, Alireza Rezaei Mahdiraji, Ziawasch Abedjan, Tilmann Rabl, and Volker Markl

German Research Center for Artificial Intelligence

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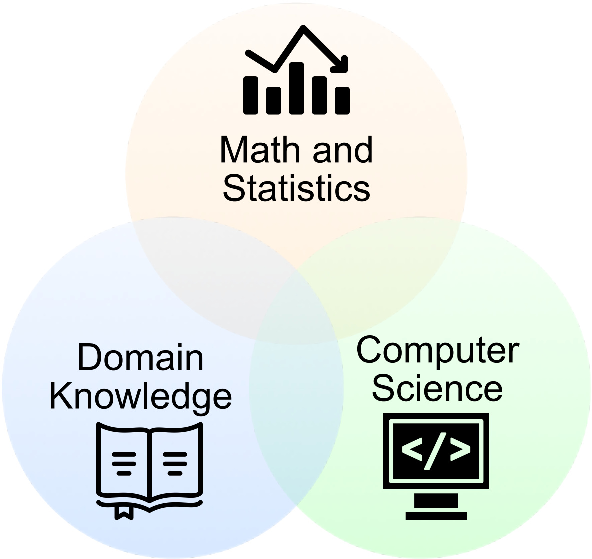
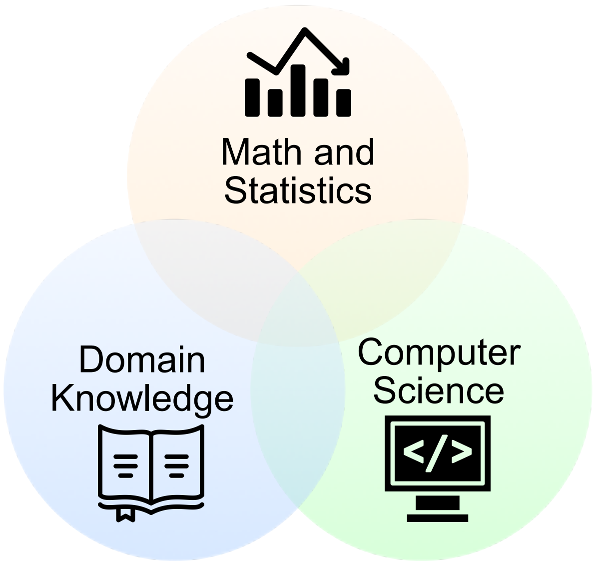
Introduction



Data Science and Machine Learning

Introduction



Data Science and Machine Learning

Data Science and ML Toolkit

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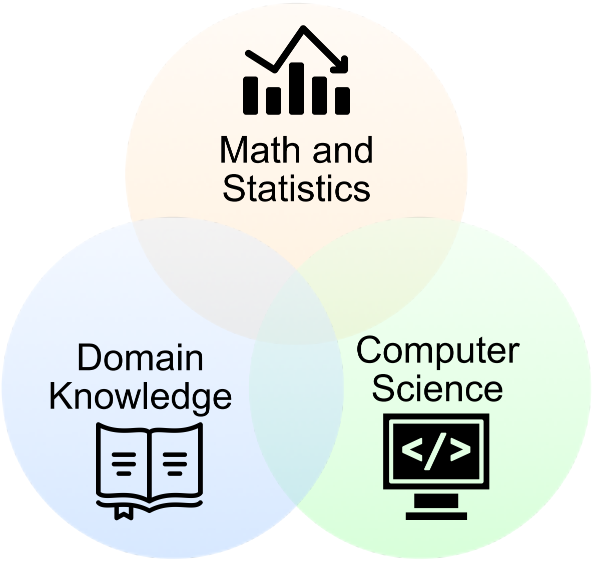

Data Science and Machine Learning

Data Science and ML Toolkit

High-quality DS and ML applications require effective collaboration

Collaborative DS and ML

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- Jupyter Notebooks enable sharing code and results

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- Containerized environments enable execution and deployment of the notebooks

[1]

1. https://www.docker.com/

Collaborative DS and ML

- Jupyter Notebooks enable sharing code and results
- Containerized environments enable execution and deployment of the notebooks
- Platforms, such as Google Colab and Kaggle, enable effective collaboration among data scientists

[1]

[2]

[3]

1. https://www.docker.com/
2. https://colab.research.google.com/
3. https://www.kaggle.com/

Problems

Lack of generated data artifacts management

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Re-execution of existing notebooks

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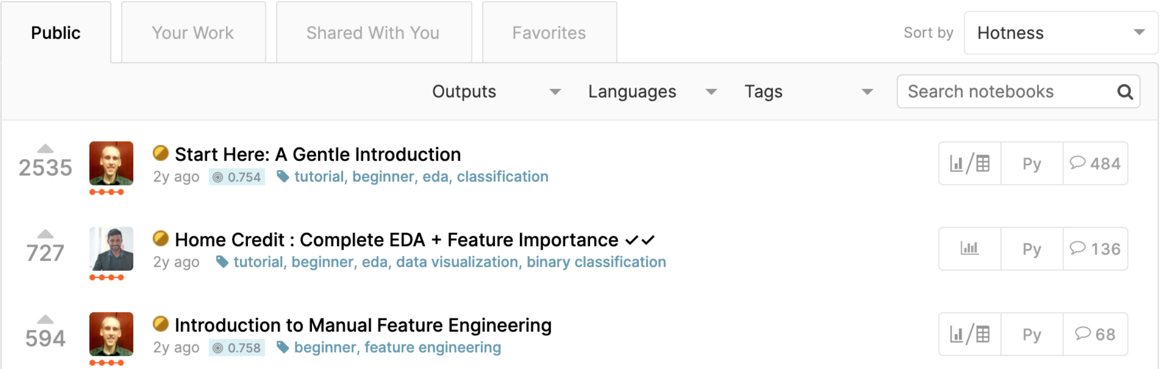

Top 3 notebooks of Home Credit Default Risk Kaggle Competition[1] generate 100s GBs of intermediate data artifact and are copied 10,000 times

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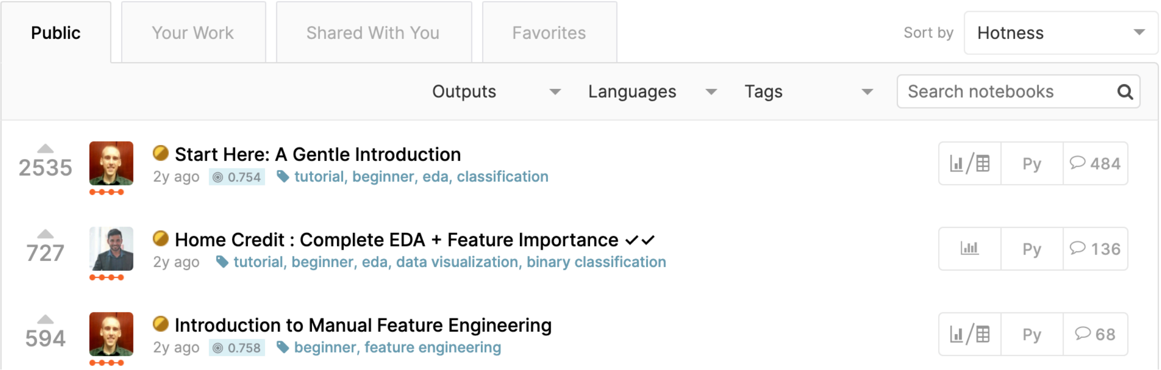

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Lack of **data management** in existing collaborative environment leads to **1000s of hours of redundant** data processing and model training

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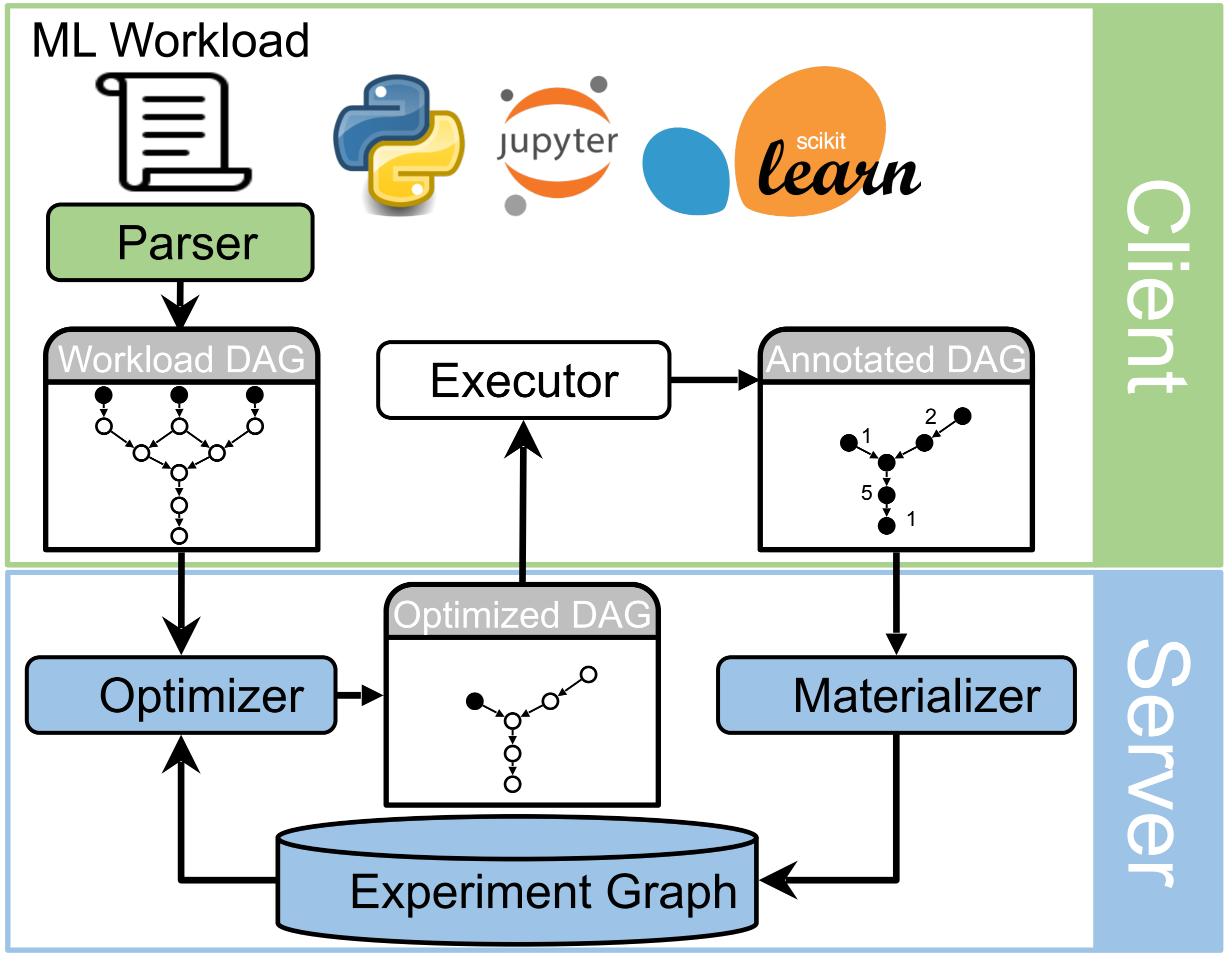
Collaborative ML Workload Optimizer



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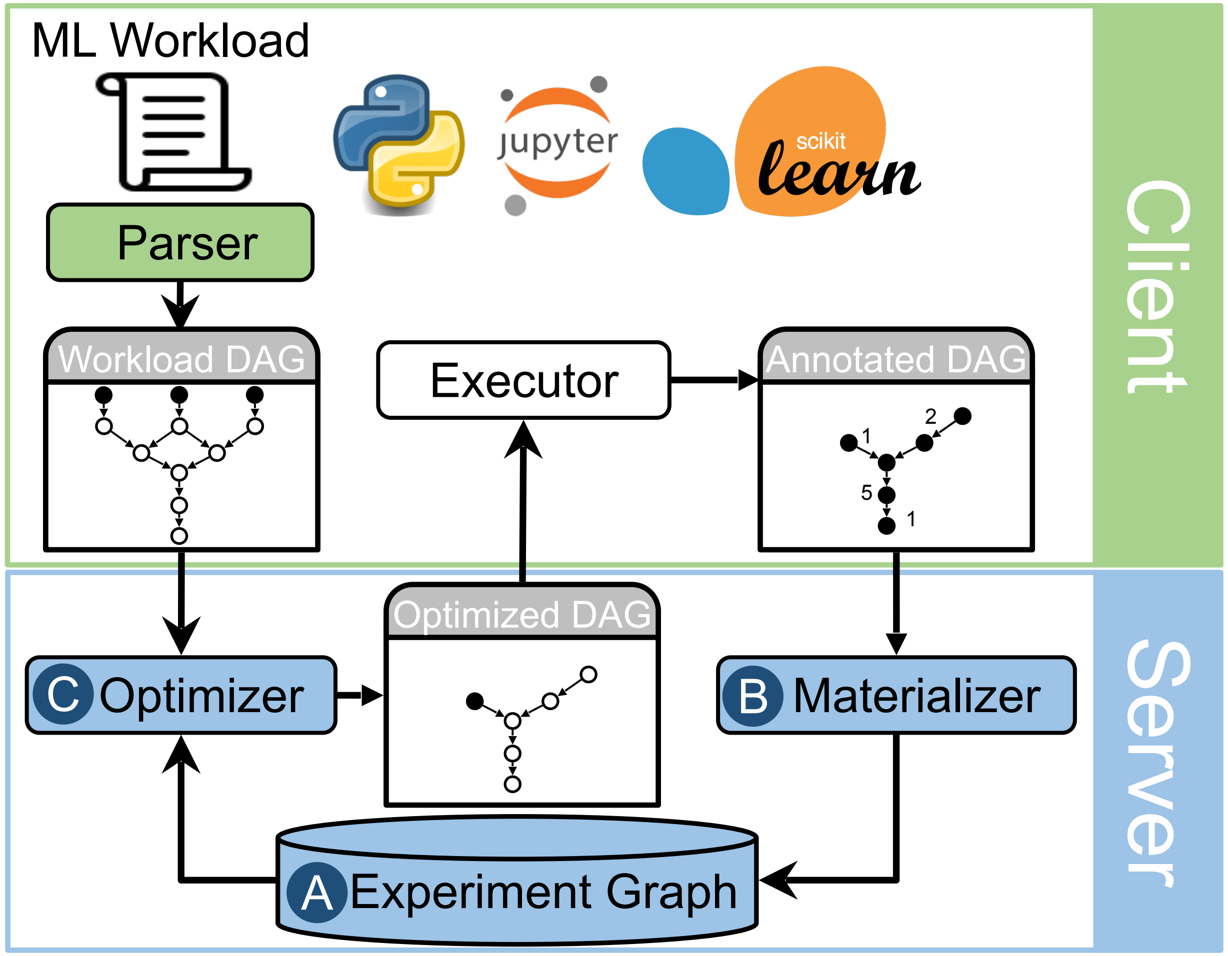

Ⓐ Experiment Graph
- Union of all the Workload DAGs
- Vertices: data artifacts
- Edges: operations

Ⓑ Materializer
- Store data artifacts with high-likelihood of future reuse

Ⓒ Optimizer
- Linear-time reuse algorithm
- Finds optimal execution DAG

Materialization Problem

Given a **storage budget**, materialize a subset of the artifacts in order to minimize the **execution cost**

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Challenges:

1. Future workloads are unknown
2. Even if future workloads are known a priori, the problem is NP-Hard (Bhattacherjee, 2015)
3. Accommodating large graphs and fast number of incoming workloads

Materialization Algorithm

For every artifact compute a ***utility*** value: ↓ **size** ↑ **run-time** **frequency** **potential**

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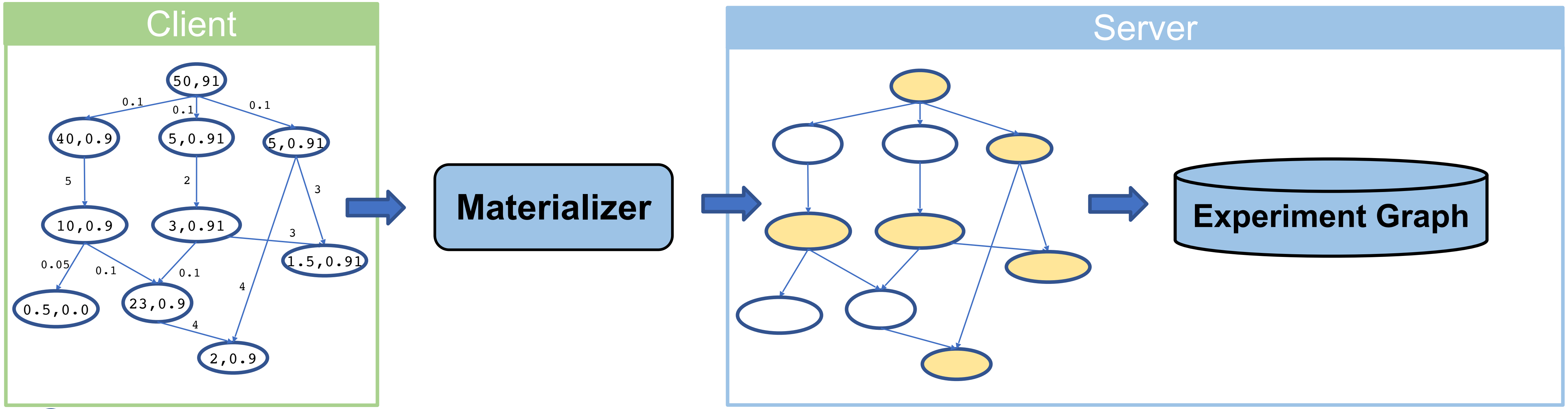


Materialized artifact

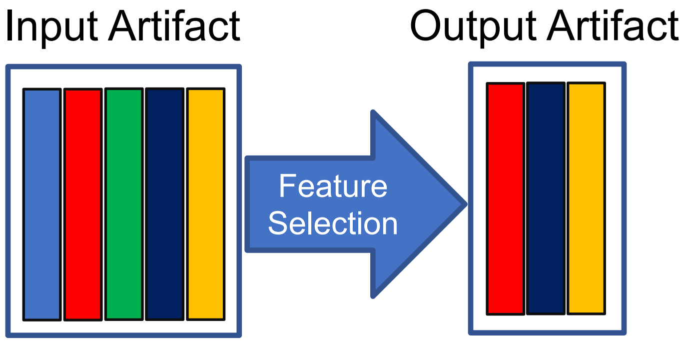
Un-materialized artifact

Storage-aware Materialization

- Many **duplicated** columns in intermediate data artifacts

Storage-aware Materialization

- Many **duplicated** columns in intermediate data artifacts
  - Feature selection operations
  - Feature generation operations



Storage-aware Materialization

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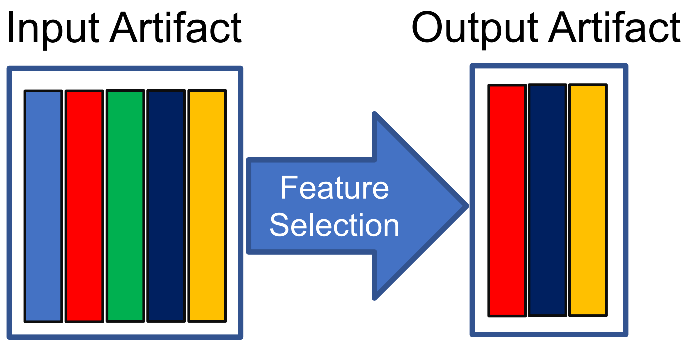
- Apply column deduplication strategy

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Storage-aware Materialization
while budget is not exhausted:
    1. run materialization algorithm
    2. deduplicate the materialized artifacts
    3. update the size of unmaterialized
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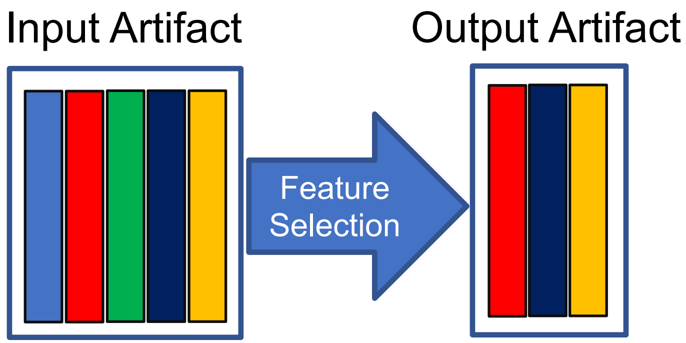

Storage-aware Materialization
while budget is not exhausted: 1. run materialization algorithm 2. deduplicate the materialized artifacts 3. update the size of unmaterialized

Improves Storage utilization and Run-time

Reuse Problem

Given **EG** and a **new workload**, find the set of workload artifacts to **reuse** from EG and the set of artifact to **compute**

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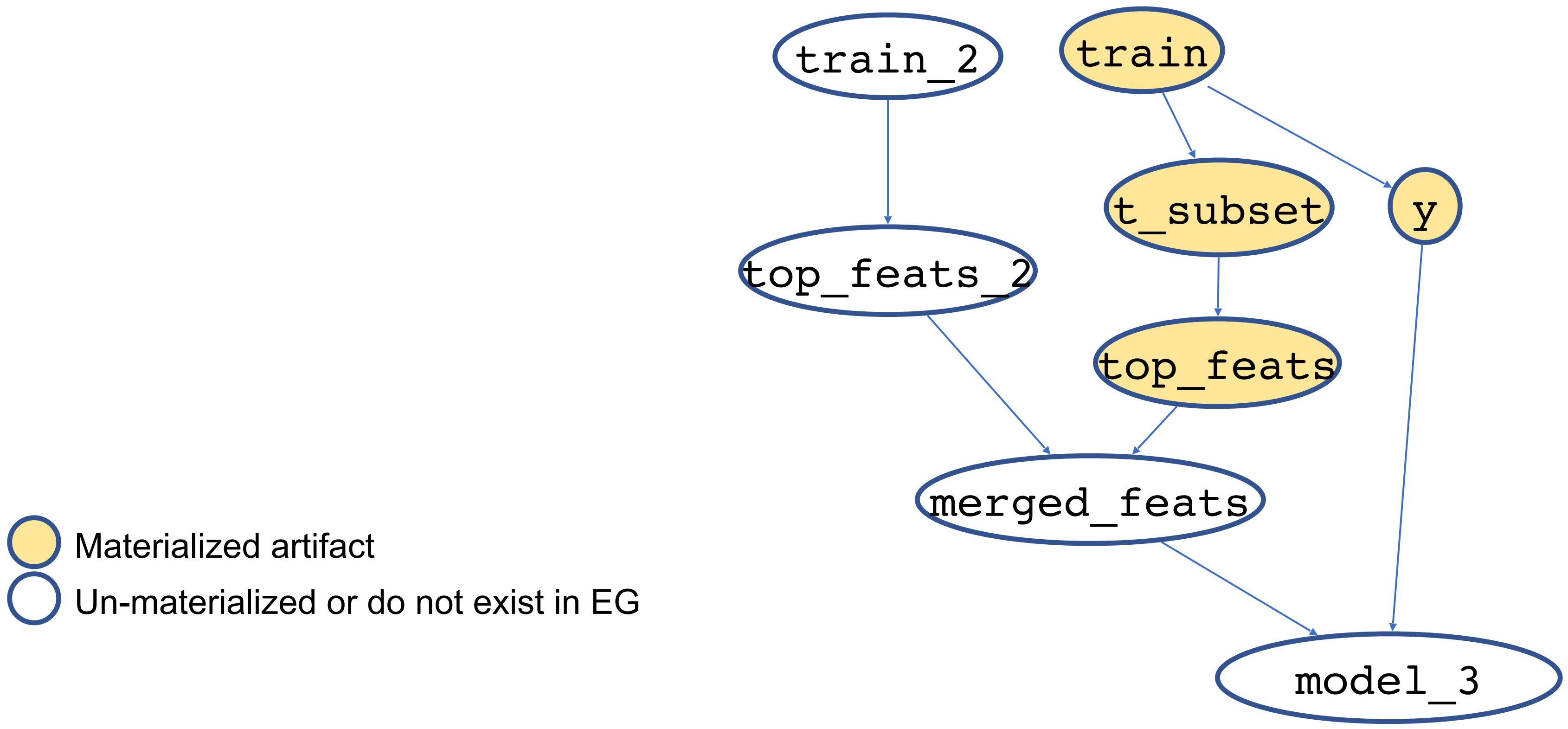
Given **EG** and a **new workload**, find the set of workload artifacts to **reuse** from EG and the set of artifact to **compute**

Challenges:

1. Exponential time complexity of exhaustive search
2. Accommodating large graphs and fast number of incoming workloads, state-of-the-art has polynomial time complexity $\mathcal{O}(|\mathcal{V}|.|E|^2)$ (Helix, 2018)

Reuse Algorithm

A linear-time algorithm to compute optimal execution plan with a ***forward and backward pass*** on the workload DAG



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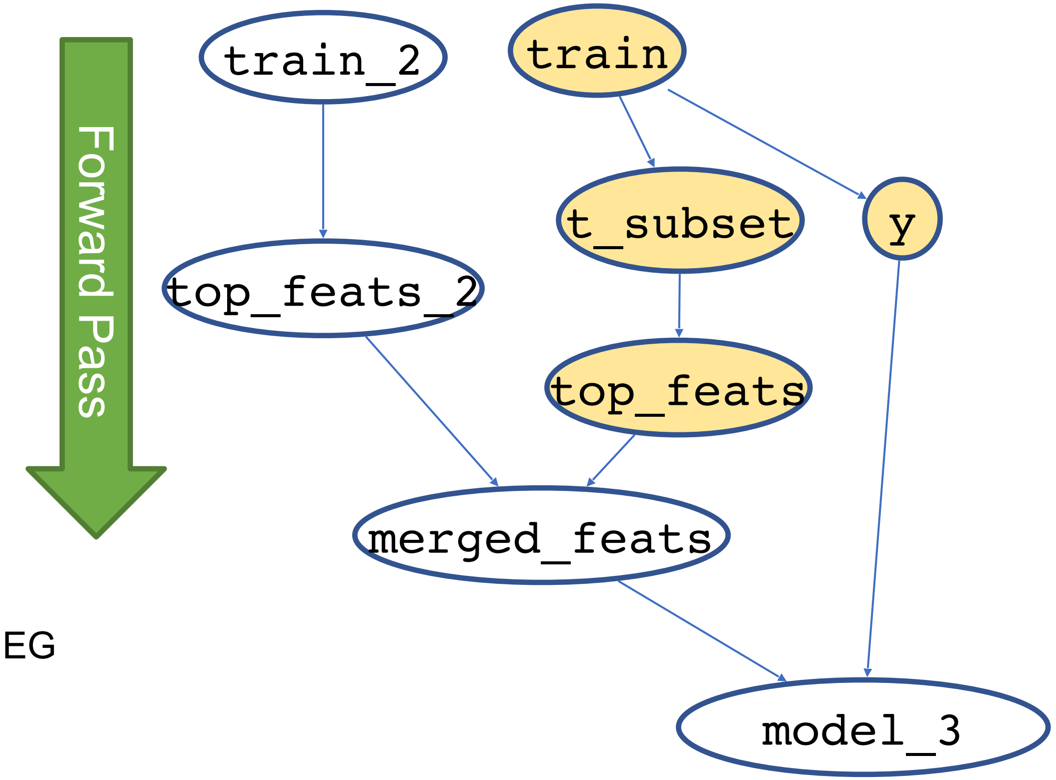
A linear-time algorithm to compute optimal execution plan with a ***forward and backward pass*** on the workload DAG

- Accumulate run-times
- For every vertex
  - Load or compute



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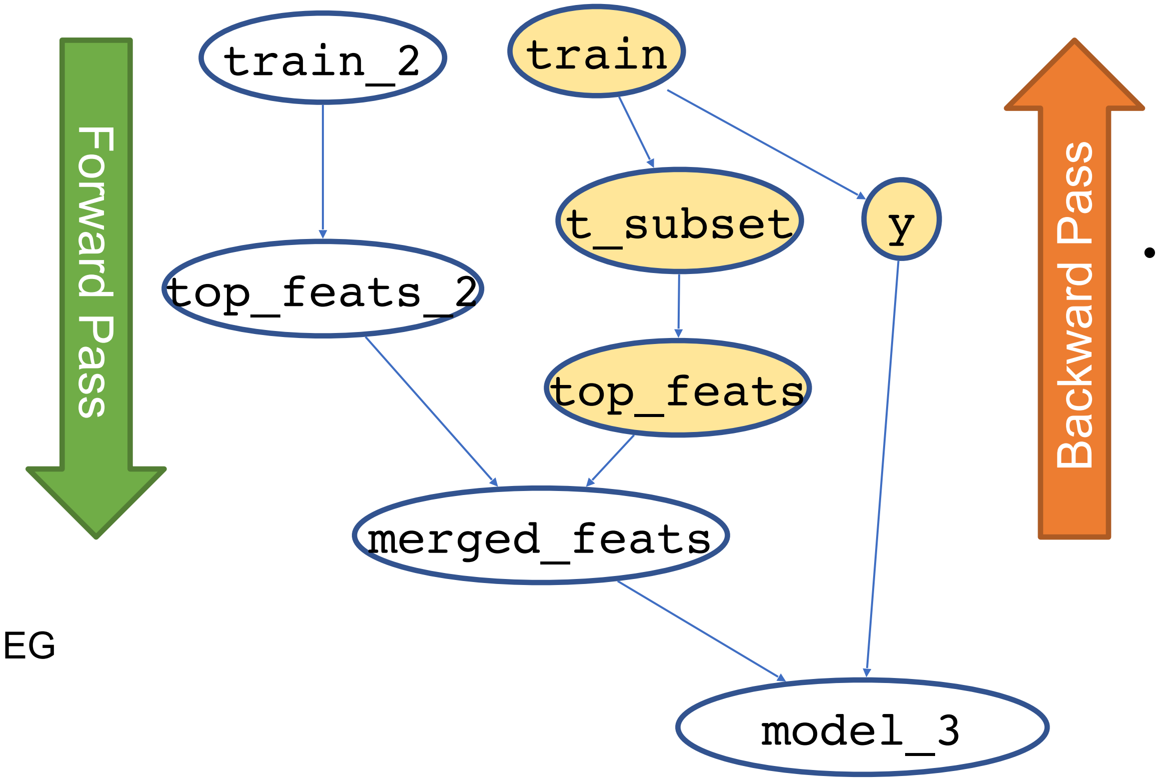

- Prune unnecessary loaded vertices

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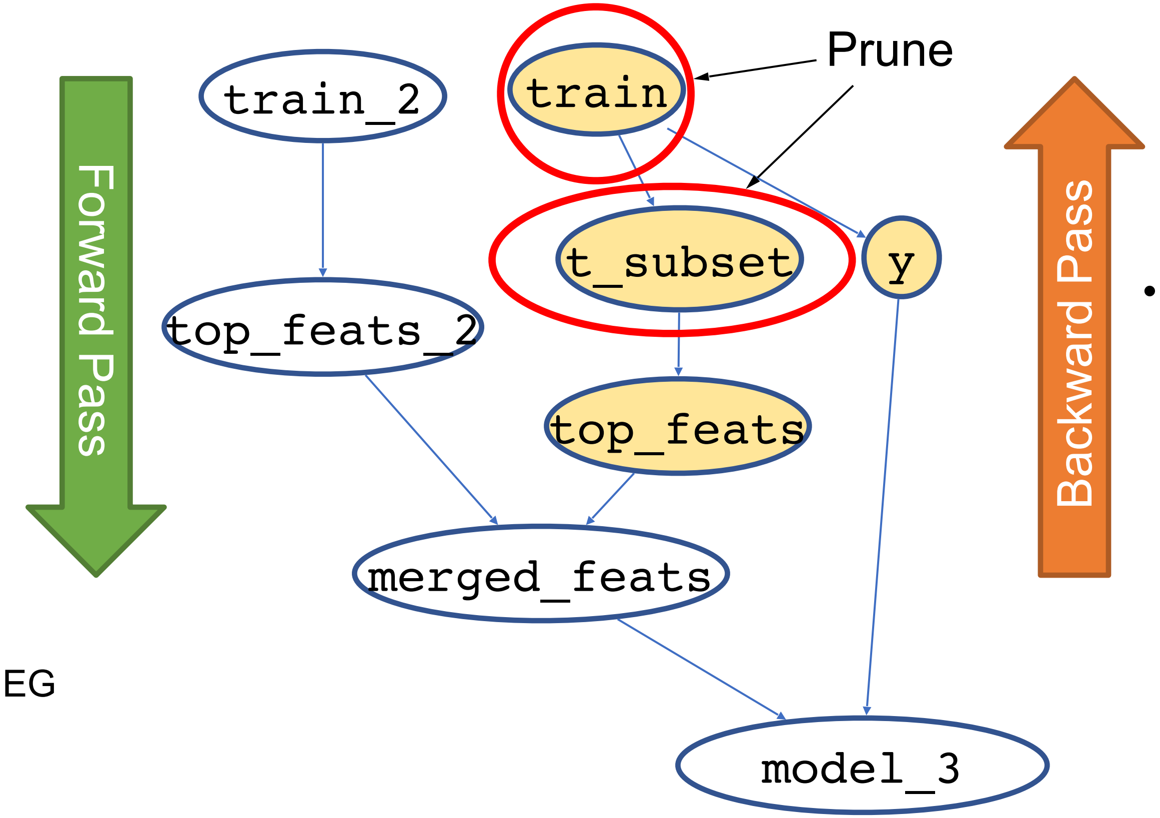

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Evaluation

Workload

- **Kaggle**
  - Kaggle Home Credit Default Risk[1] Competition
  - 9 source datasets
  - 5 real and 3 generated workloads
  - Total of 130 GB artifact sizes

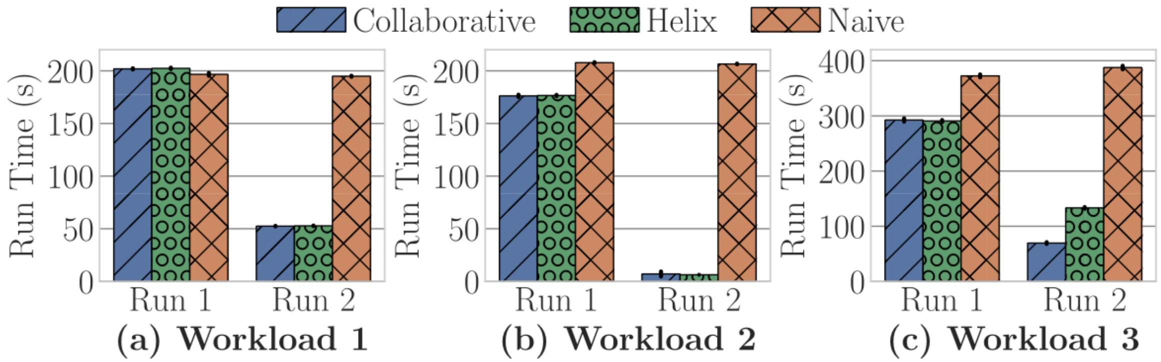
Baseline

- **Helix**
  - State-of-the-art iterative ML framework
  - Materialization Algorithm:
    - Only execution-time is considered
    - Nodes are not prioritized
  - Reuse Algorithm
    - Utilizes Edmonds-Karp Max-Flow algorithm, which runs in $\mathcal{O}(|\mathcal{V}|.|E|^2)$

- **Naïve**
  - No Optimization

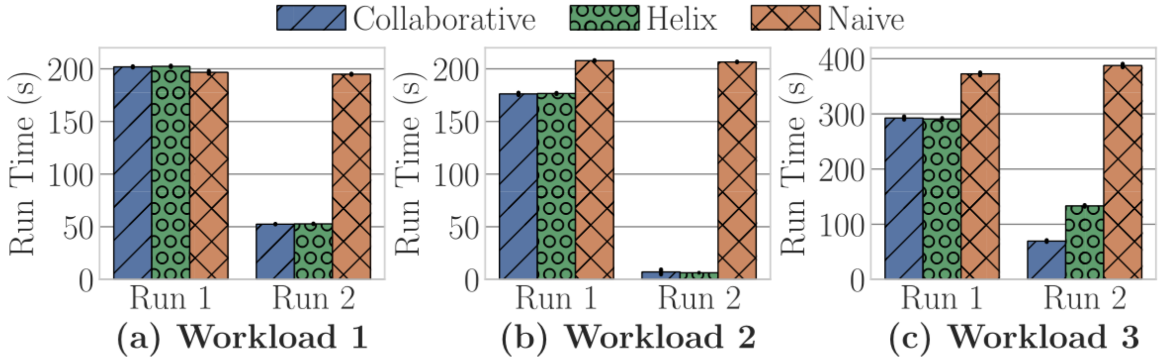
1. https://www.kaggle.com/c/home-credit-default-risk

End-to-end Run-time



Repeated executions of Kaggle workloads (materialization budget = 16 GB)

End-to-end Run-time



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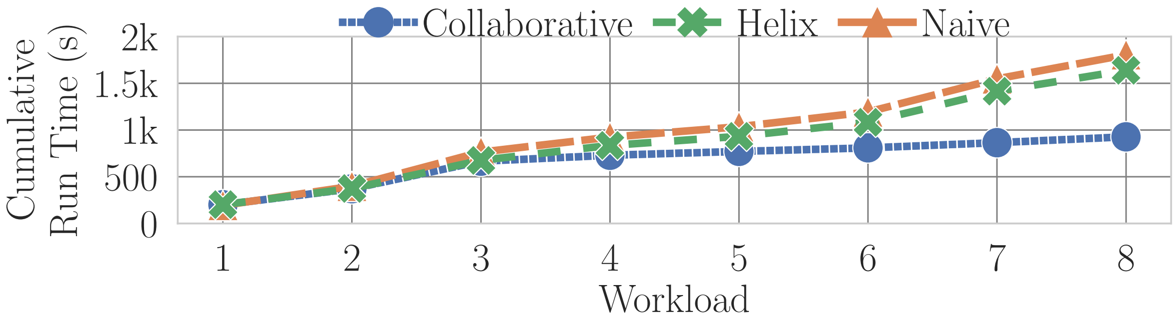

Execution of Kaggle workloads in sequence (materialization budget = 16 GB)

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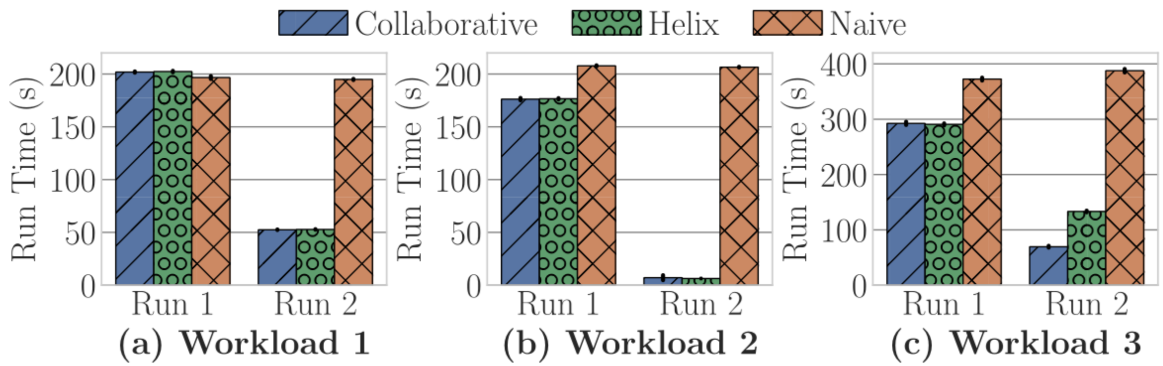

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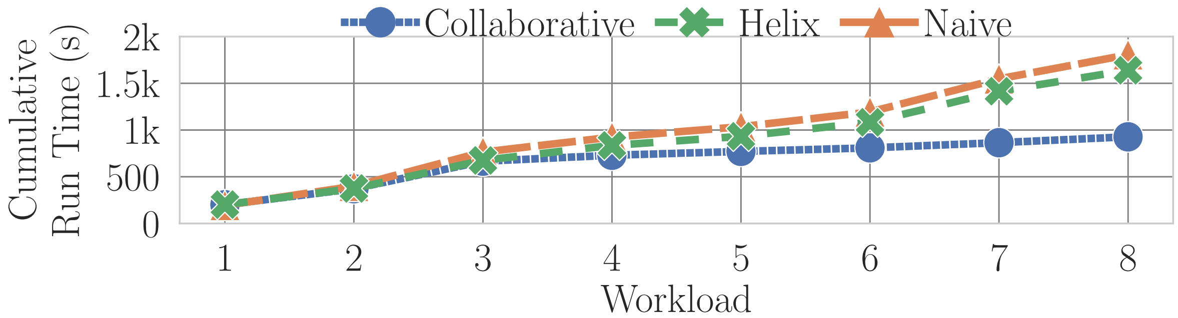
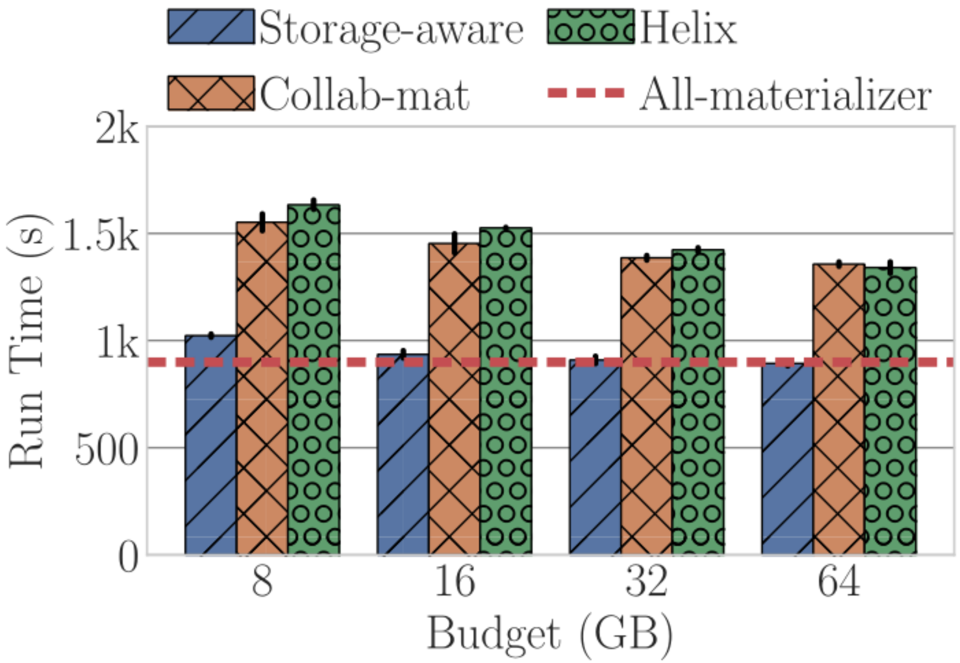


Execution of Kaggle workloads in sequence (materialization budget = 16 GB)

Optimizing ML Workloads improves run-time up to 1 order of magnitude for repeated executions and 50% for different workloads

Materialization Impact



Total run-time of the Kaggle workloads with different materialization strategies and budgets

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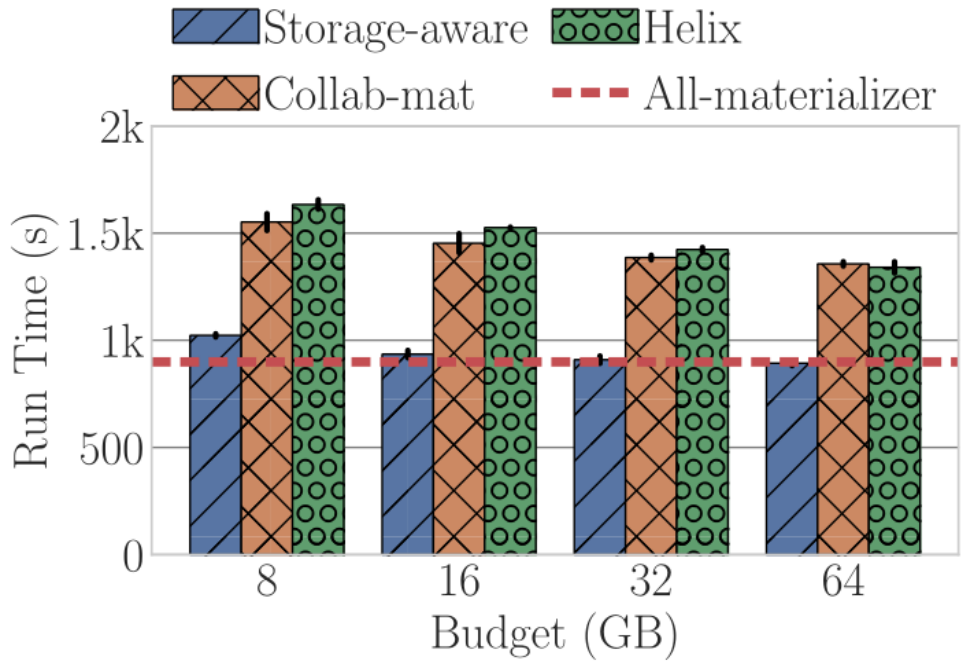
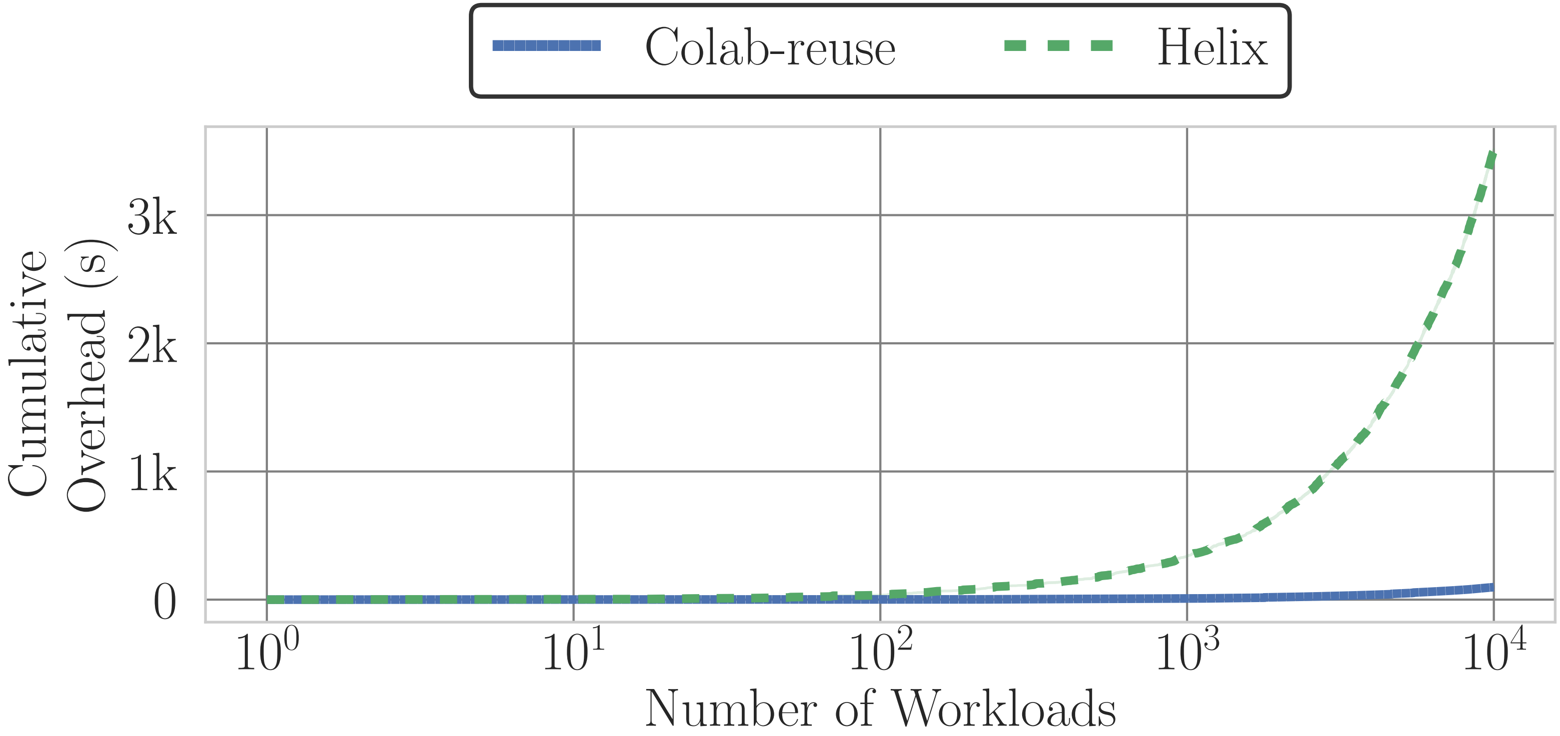
Materialization Impact



Total run-time of the Kaggle workloads with different materialization strategies and budgets

Exploiting the artifacts characteristics, such as utility and duplication rate, improves the materialization process and improves the run-time by 50%

Reuse Overhead



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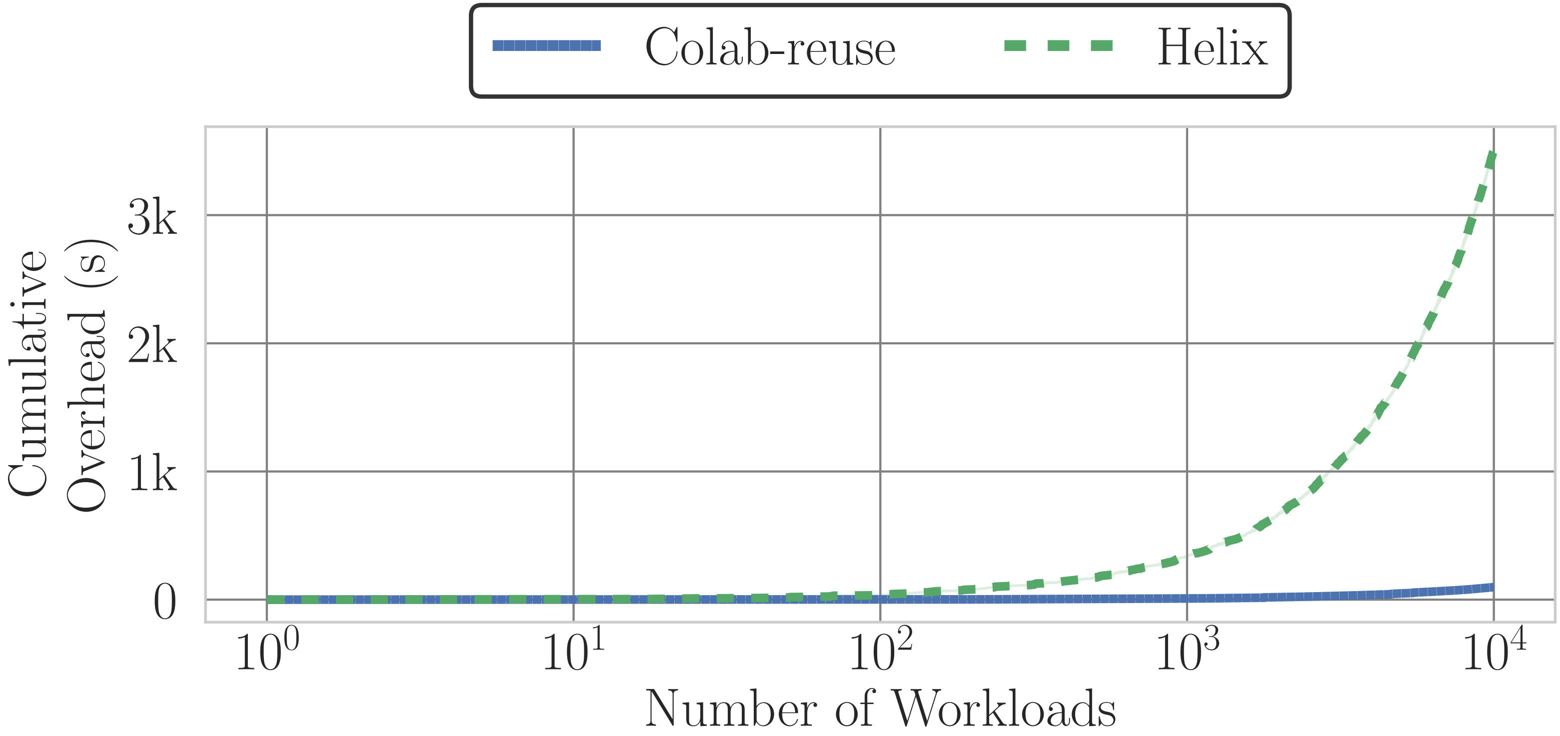
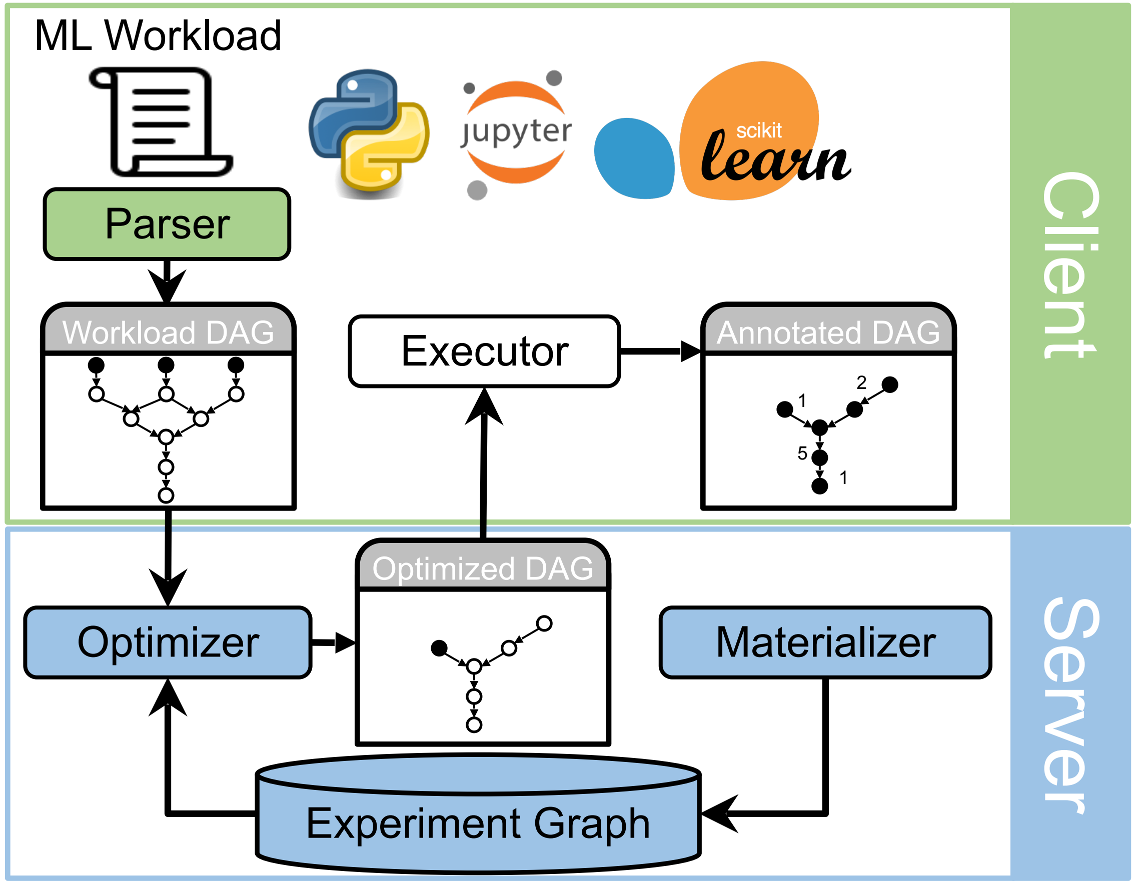


Our linear-time reuse algorithm generates a negligible overhead in real collaborative environments where 1000s of workloads are executed

Summary



- Optimization of ML workloads in collaborative environment through ***Materialization*** and ***Reuse***, while incurring negligible overhead

- **Things not covered in the talk:**
  - API and DAG Construction
  - Quality-based Materialization
  - Model Warmstarting

References

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- Burns, B., Grant, B., Oppenheimer, D., Brewer, E., & Wilkes, J. (2016). Borg, omega, and kubernetes. *Queue*, *14*(1), 70-93.

Evaluation (2)

Workload

- **Openml**
  - Classification Task 31[2]
  - 2000 scikit-learn pipelines
  - 1.5 GB of artifact sizes

DAG Construction

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train = pd.read_csv('train.csv') # [ad_desc,ts,u_id,price,y]
ad_desc = train['ad_desc']
vectorizer = CountVectorizer()
count_vectorized = vectorizer.fit_transform(ad_desc)
print count_vectorized.head()
selector = SelectKBest(k=2)
t_subset = train[['ts','u_id','price']]
y = train['y']
top_features = selector.fit_transform(t_subset, y)
model_1 = svm.SVC().fit(top_features, y)
print model_1 # terminal vertex
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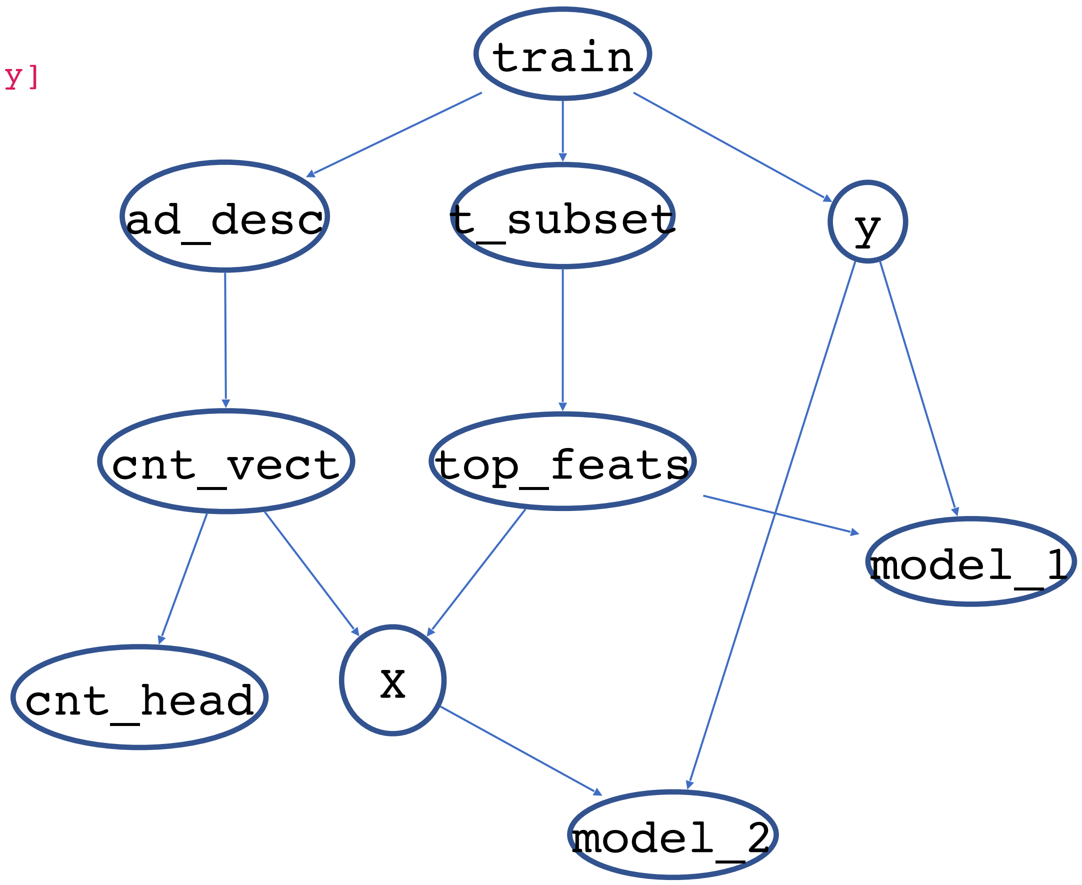

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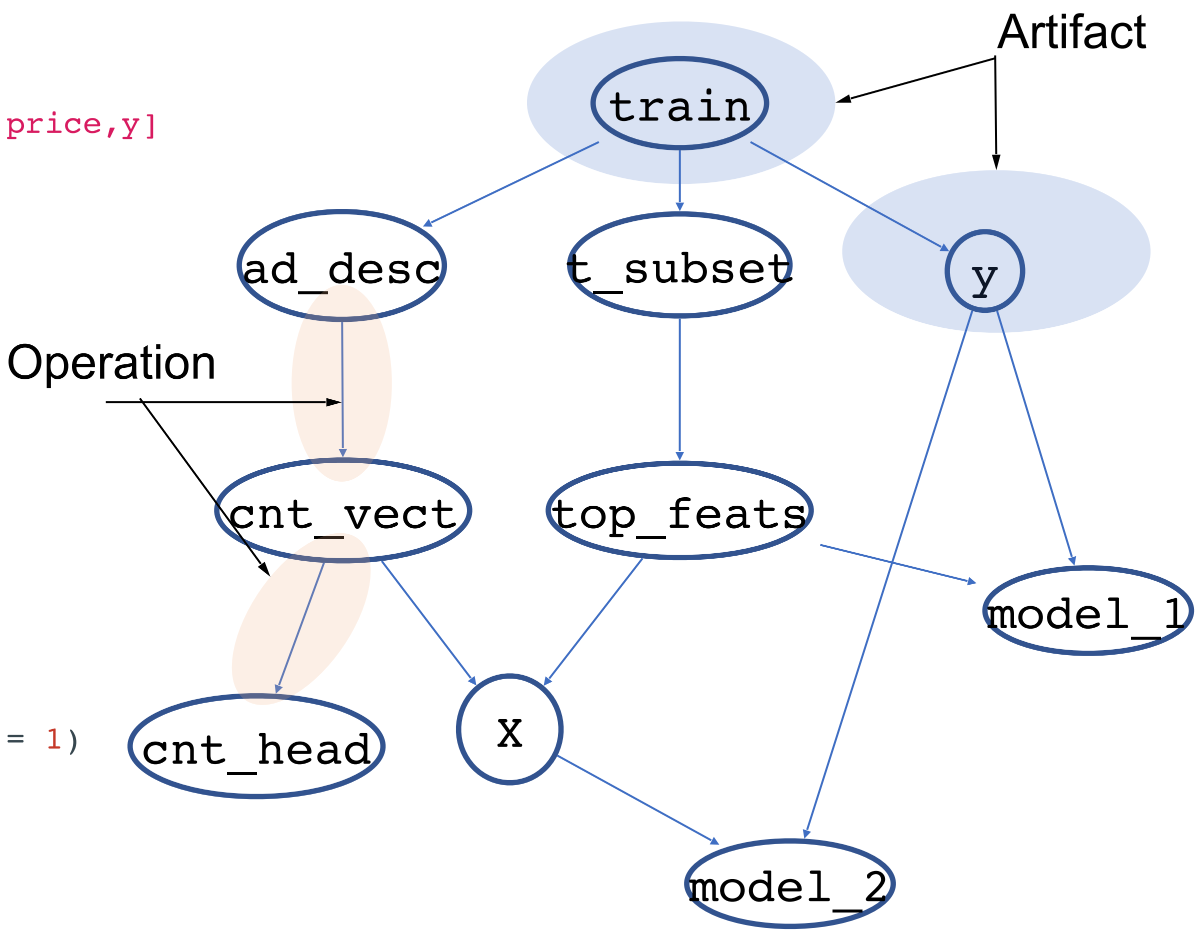

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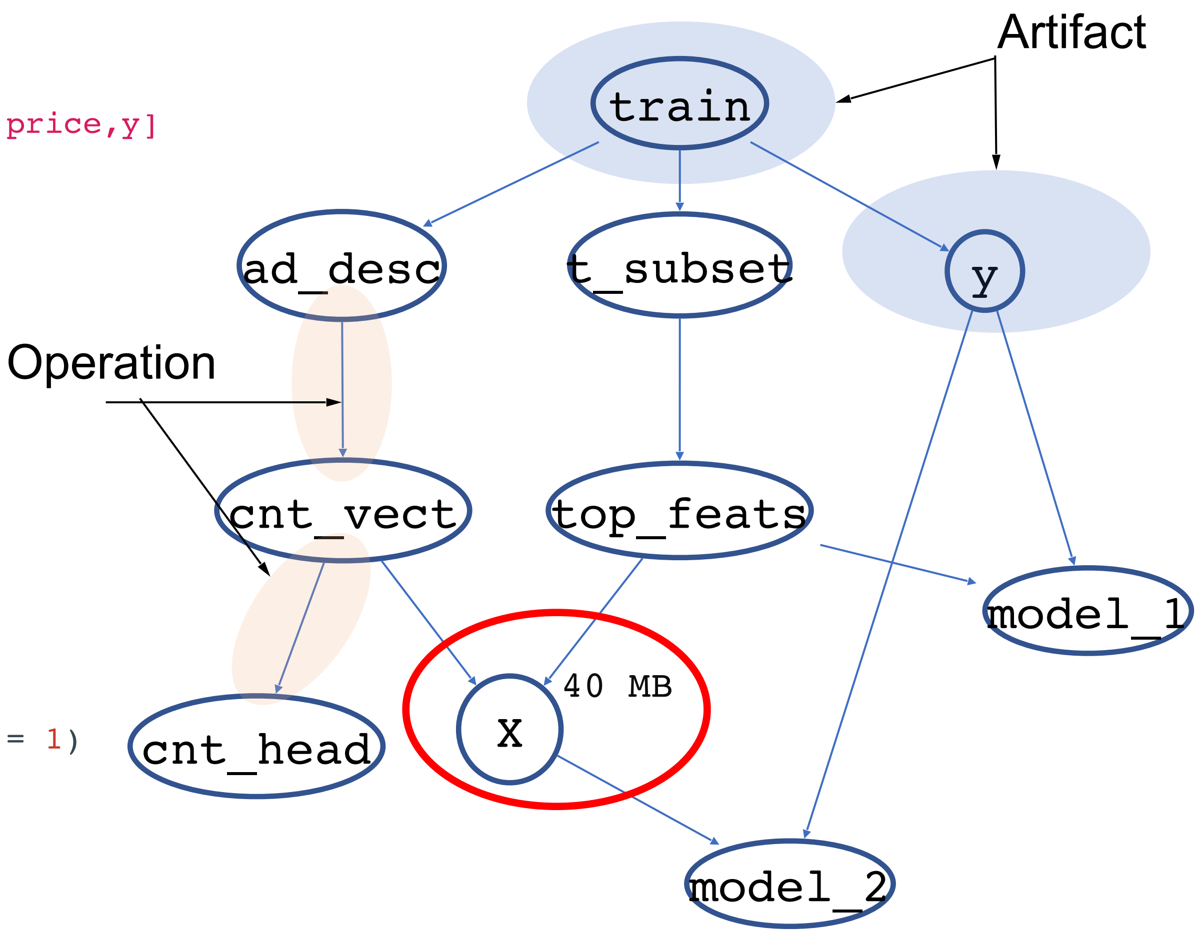

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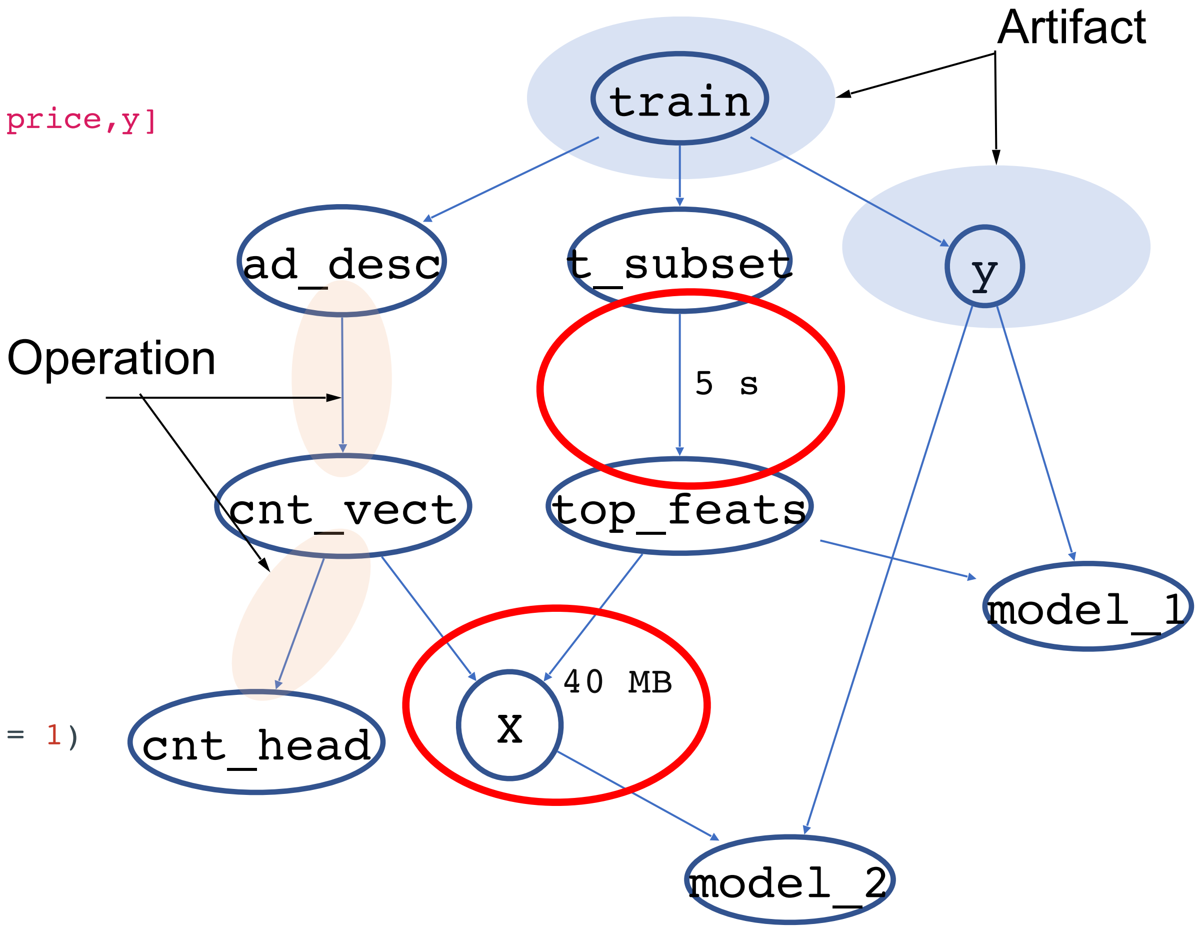

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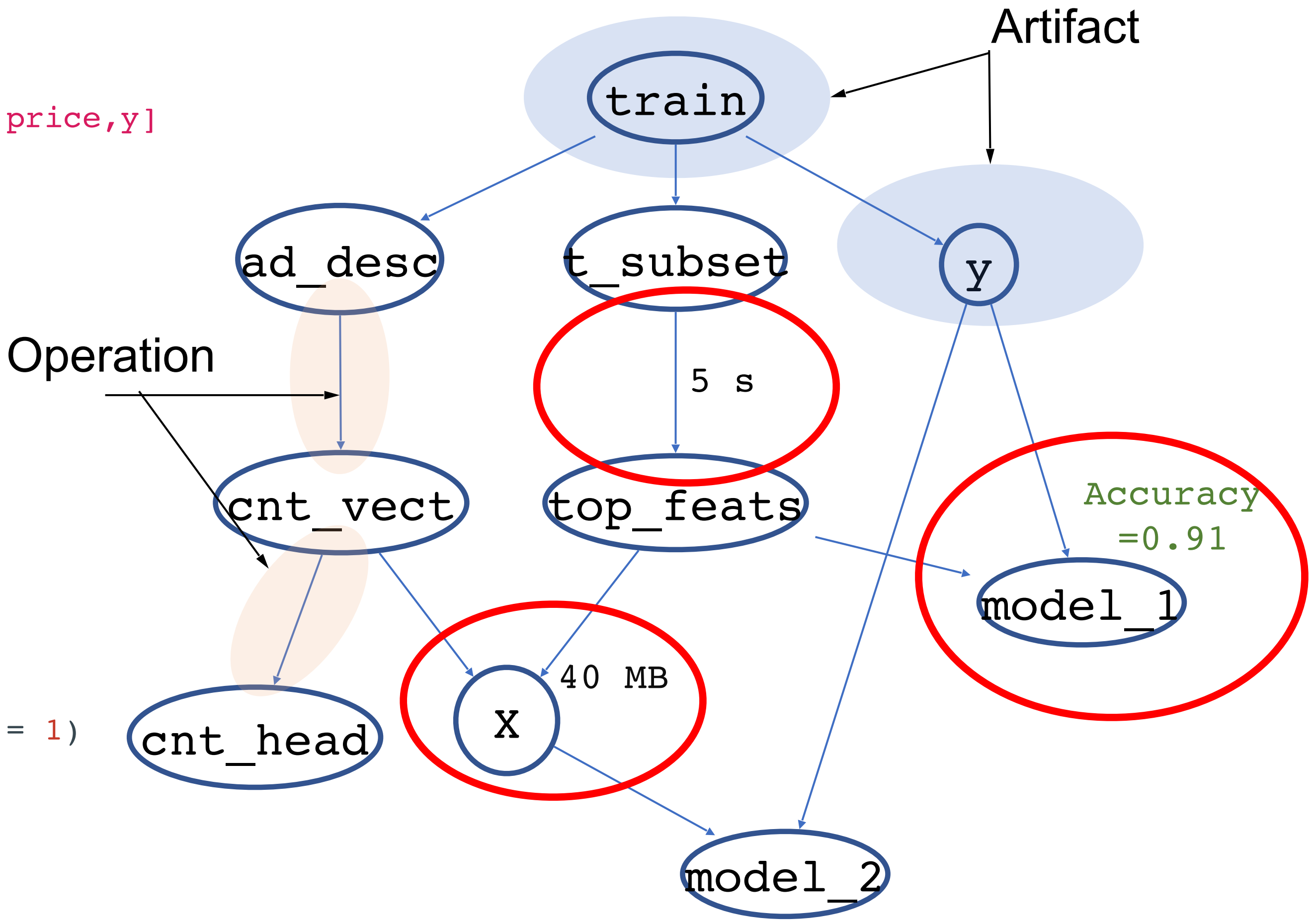

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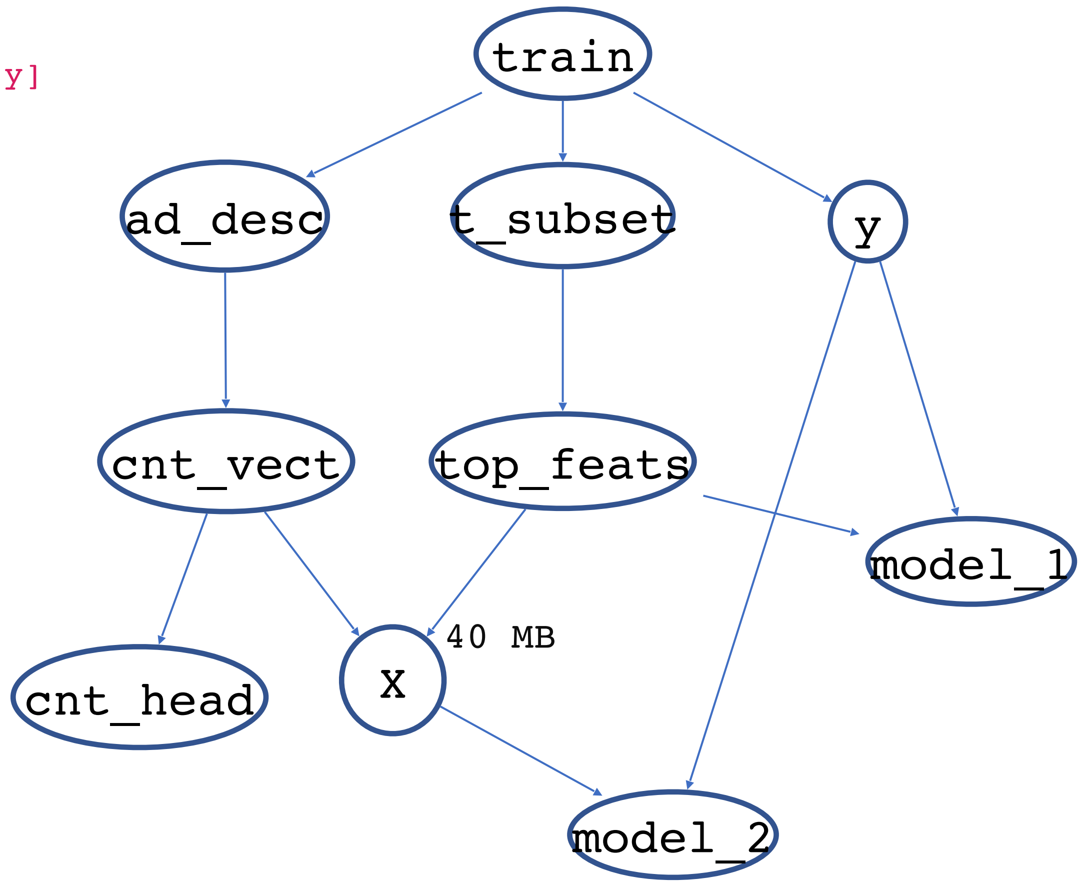

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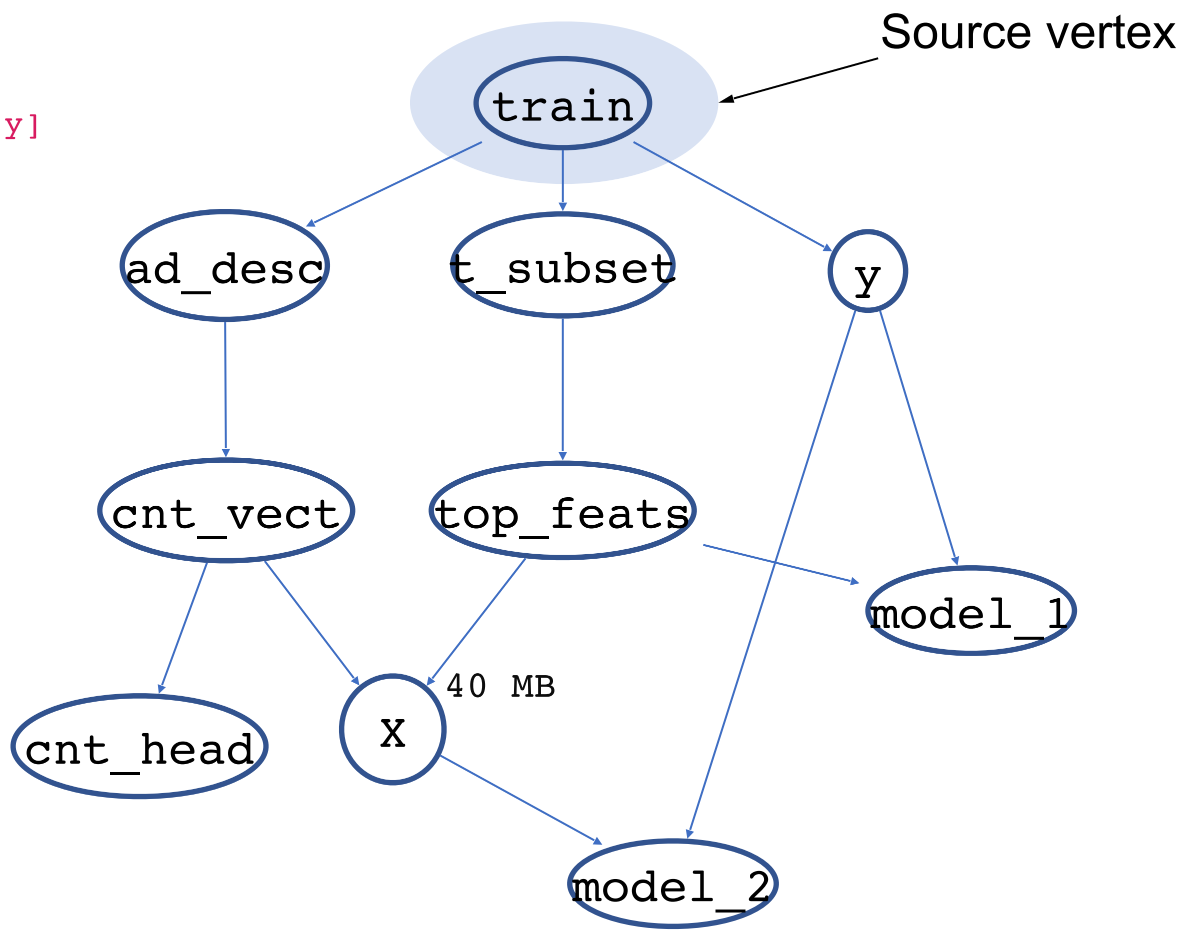

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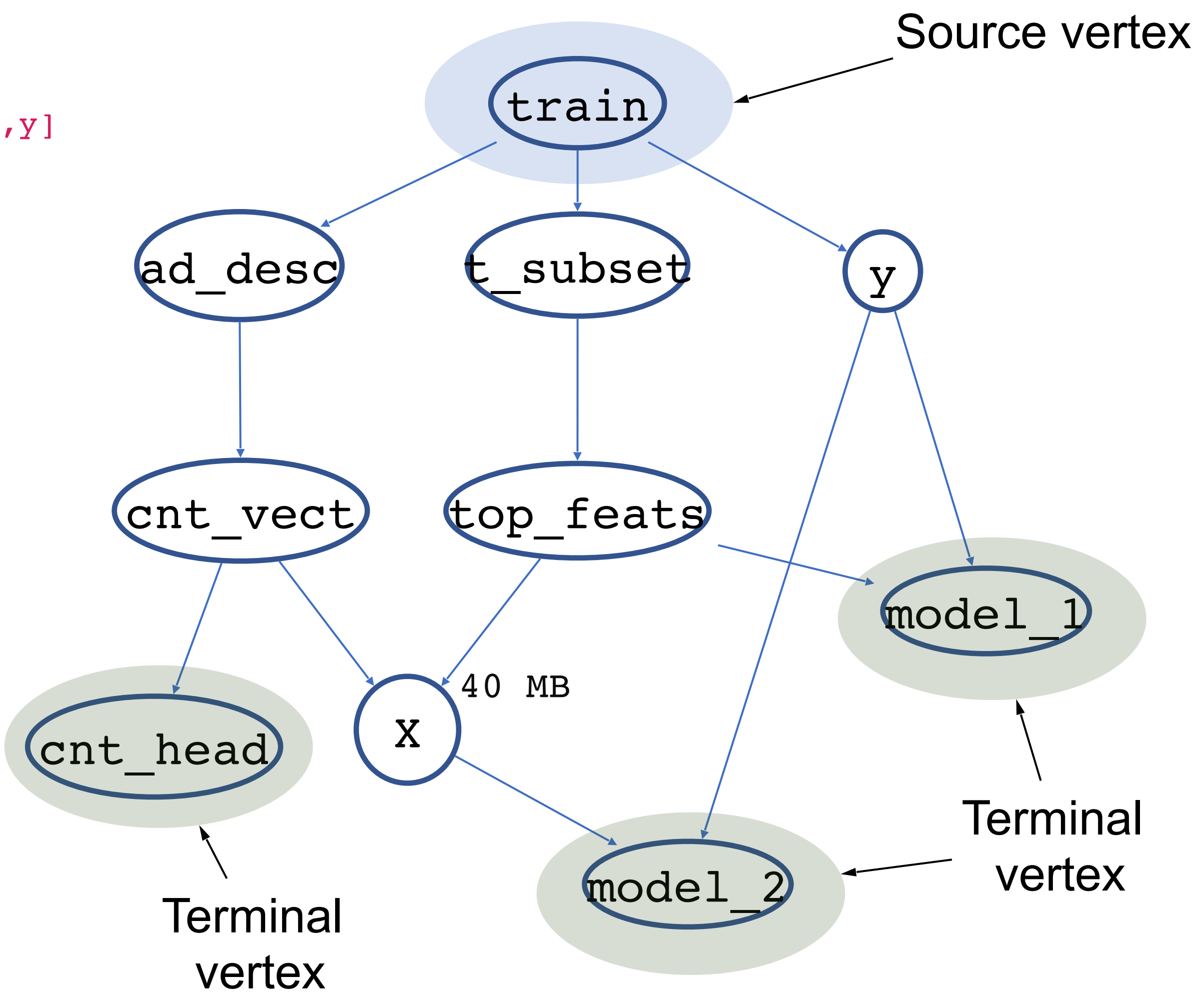

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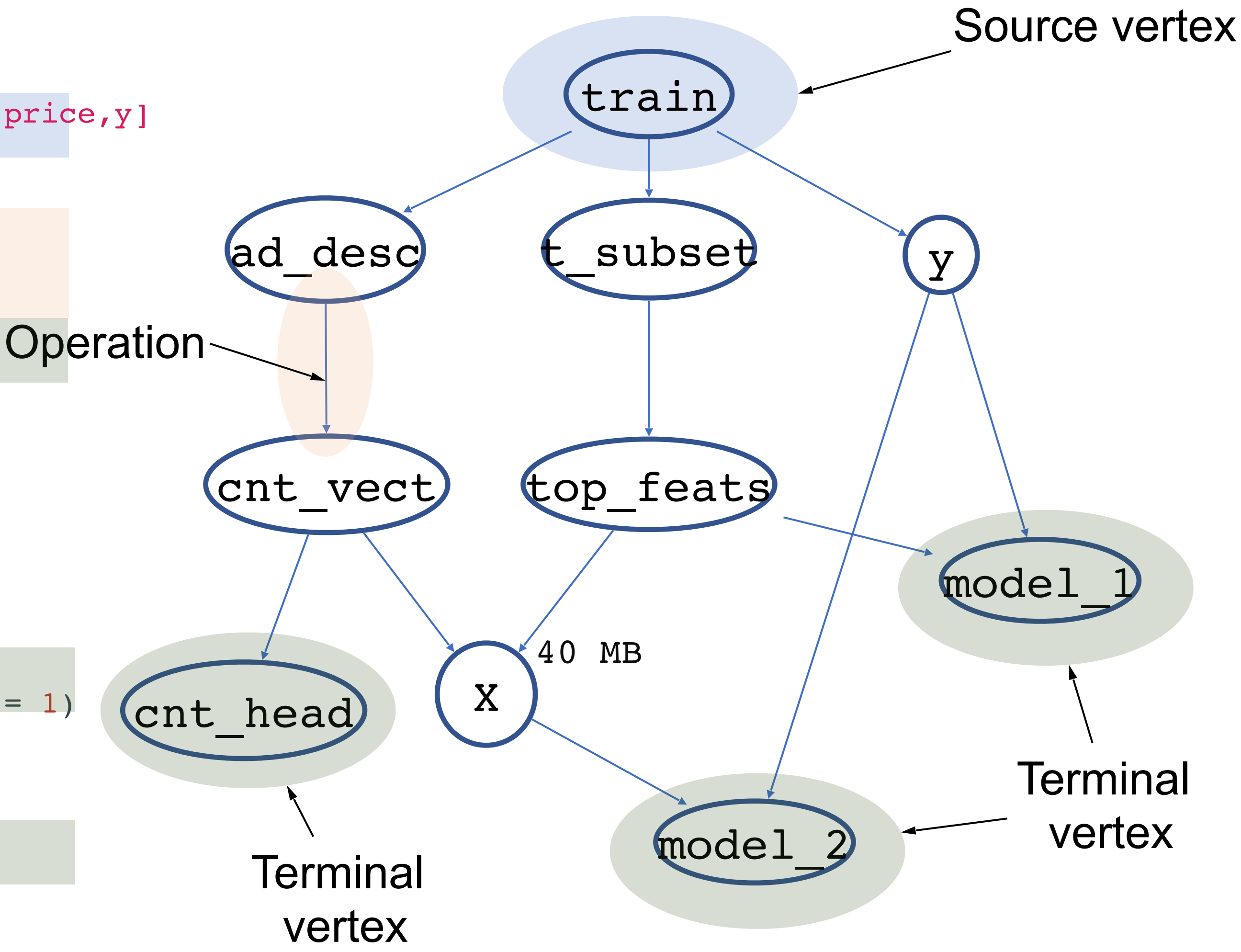
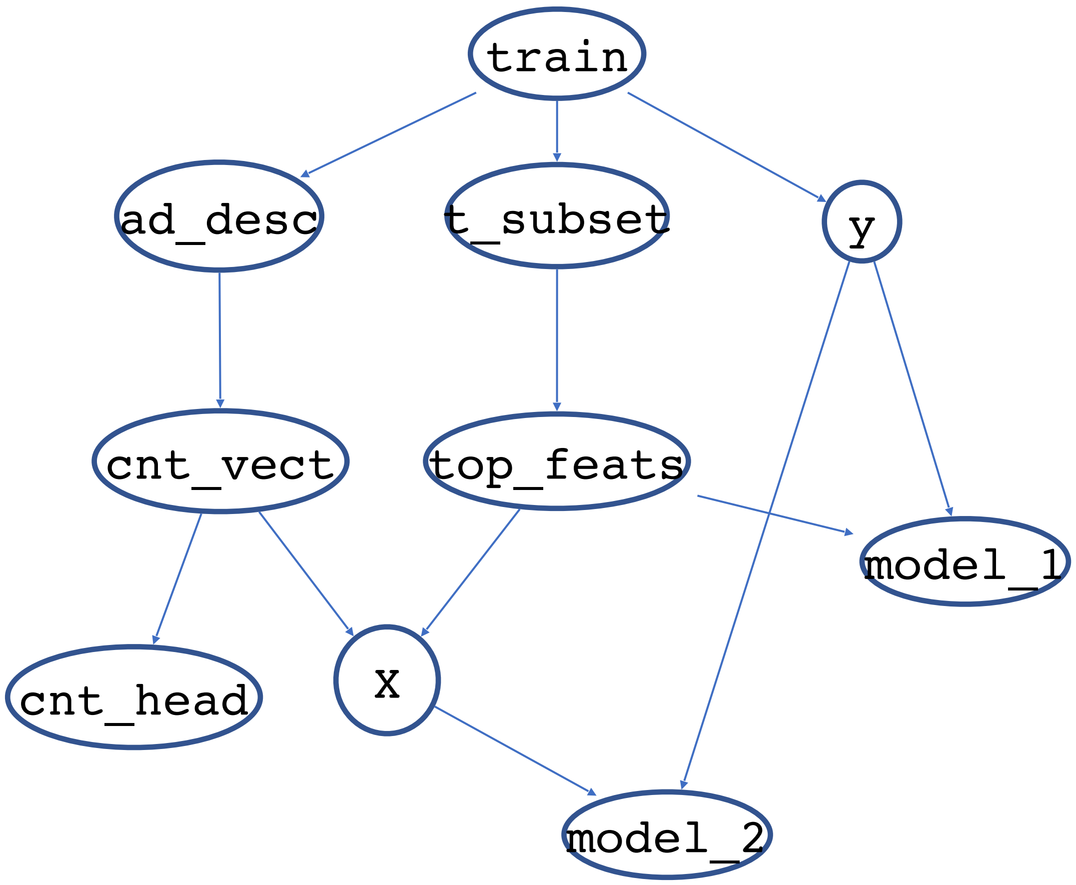
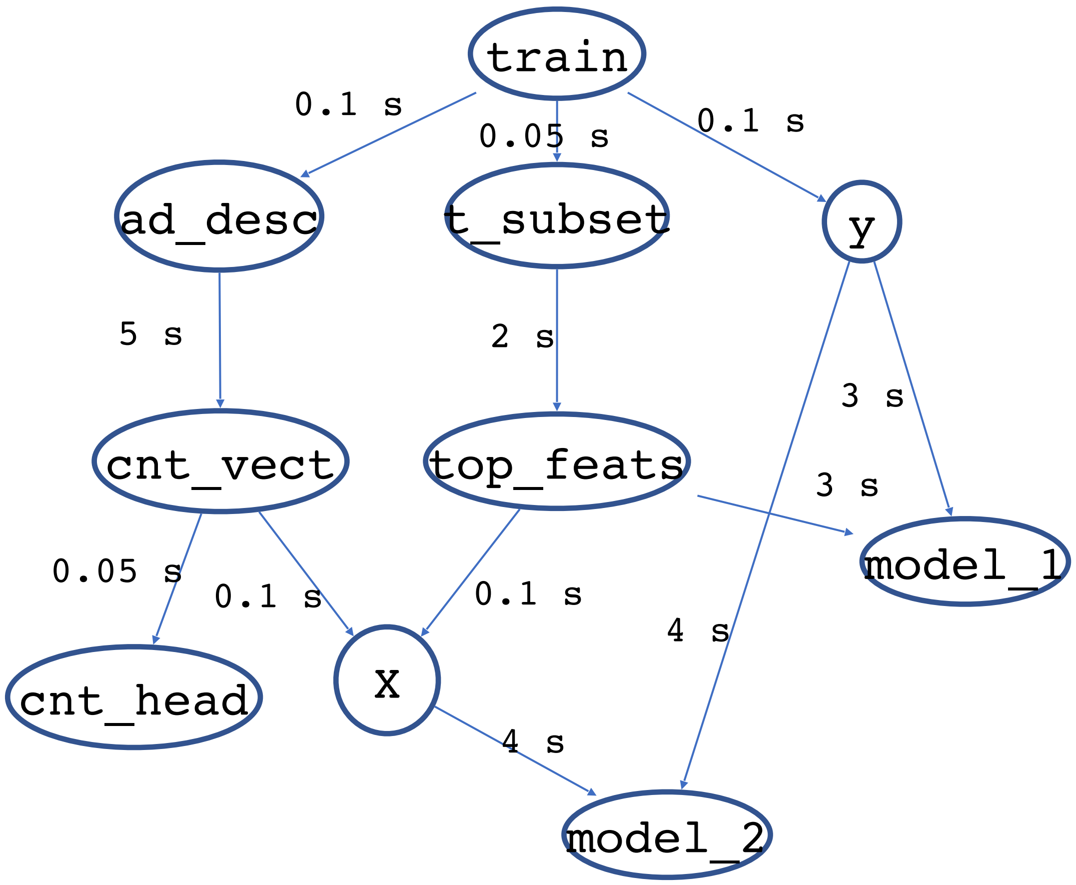


DAG Annotation



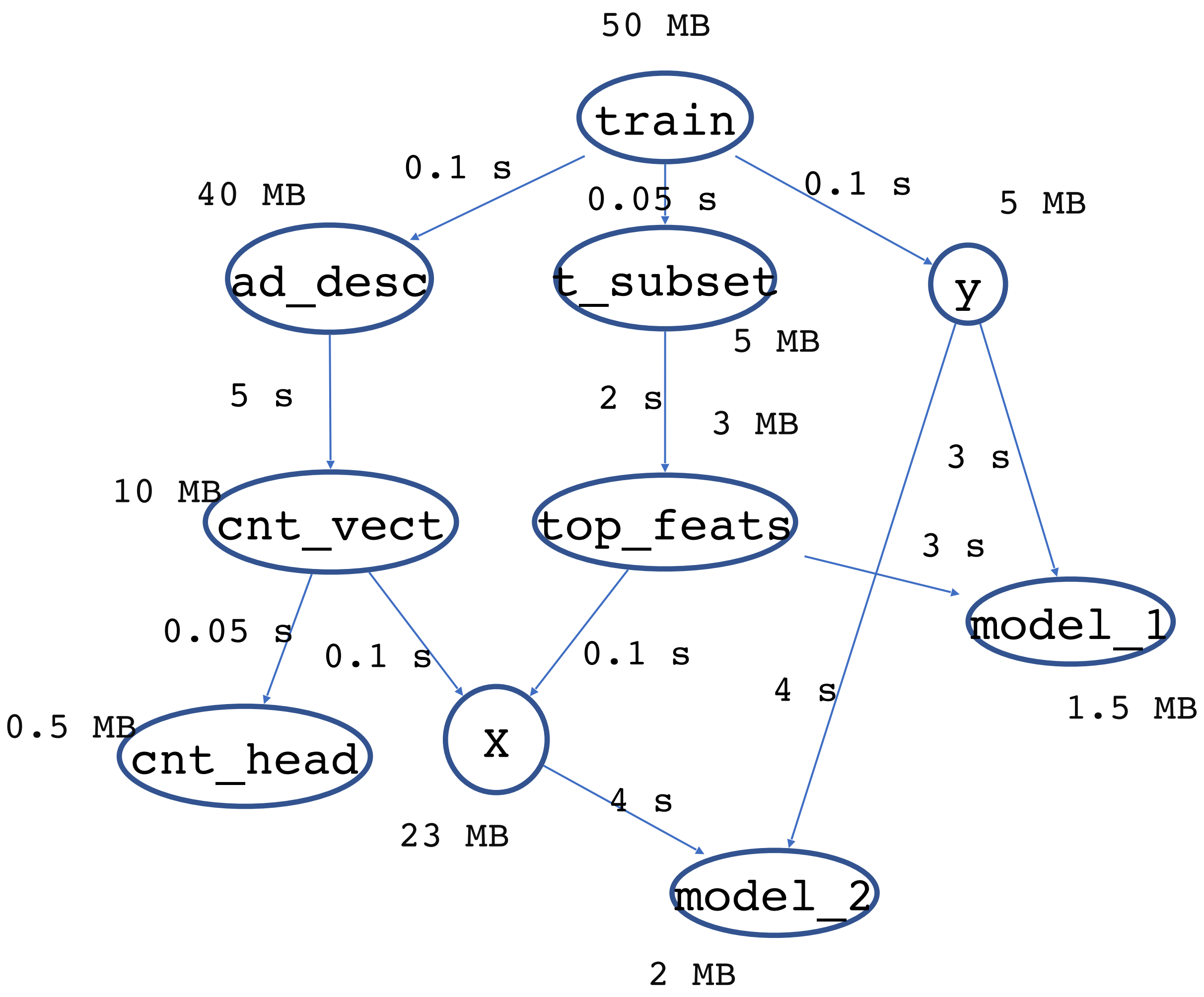
DAG Annotation

- Edge run-time



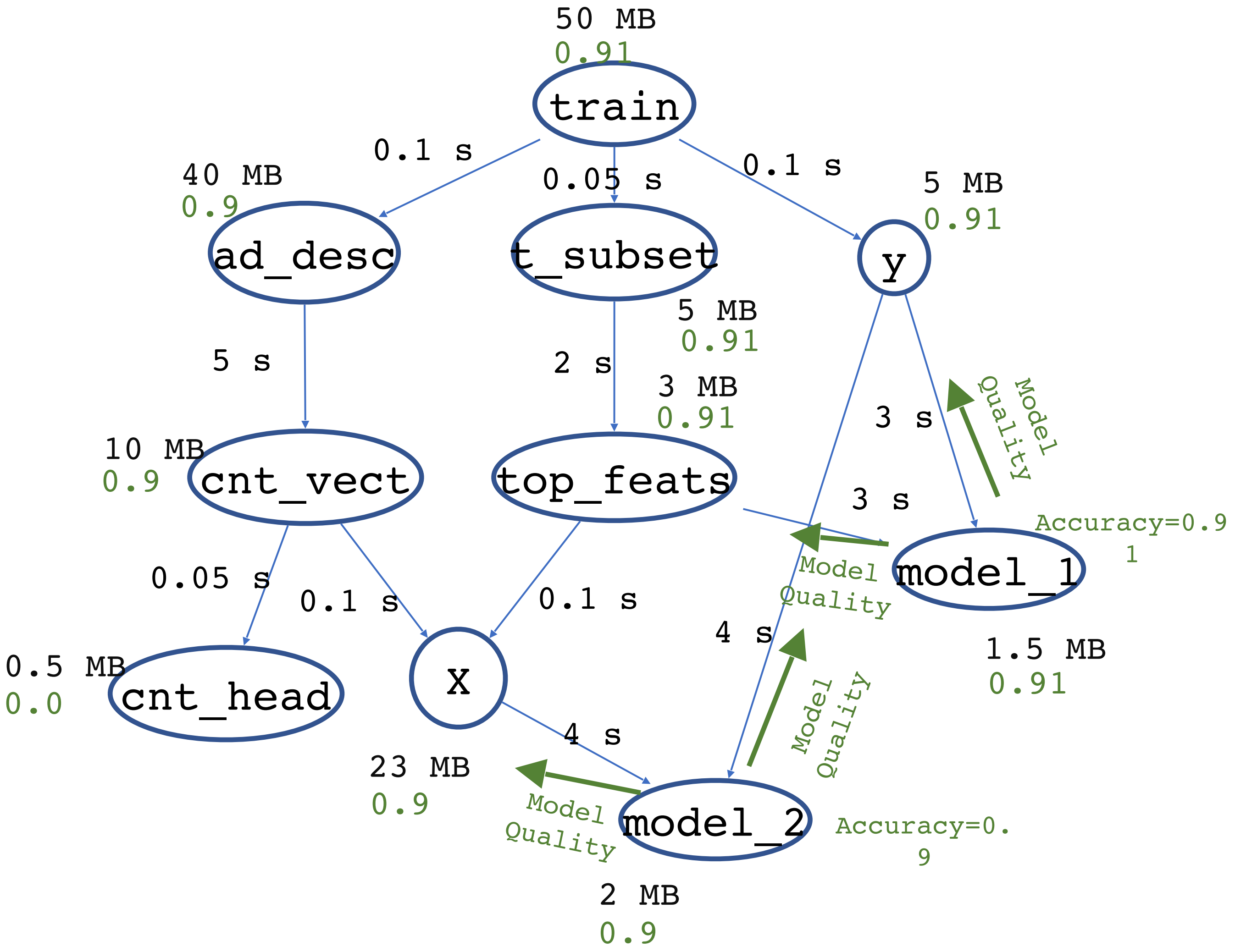
DAG Annotation

- Edge run-time
- Vertex size

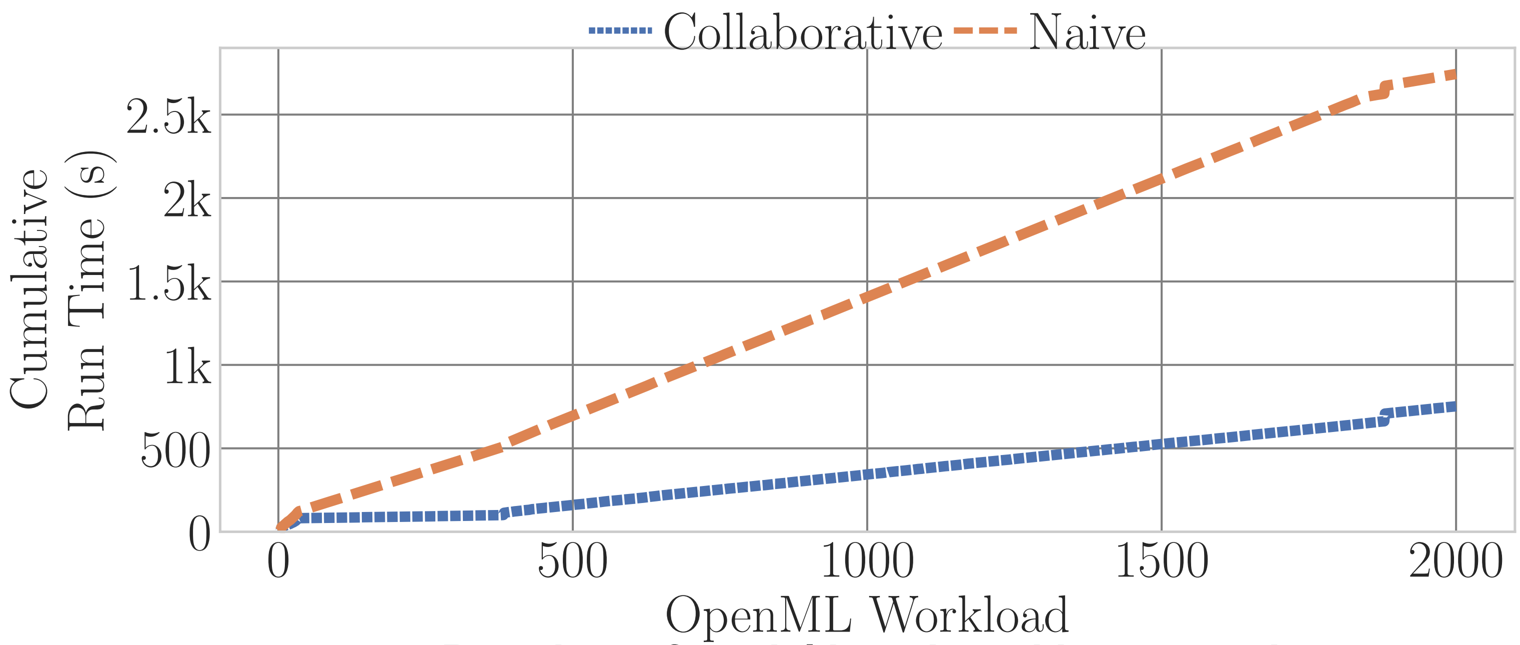


DAG Annotation

- Edge run-time
- Vertex size
- Vertex potential
    - Quality of the best reachable model



Model Materialization and Warmstarting



Run-time of model benchmarking scenario

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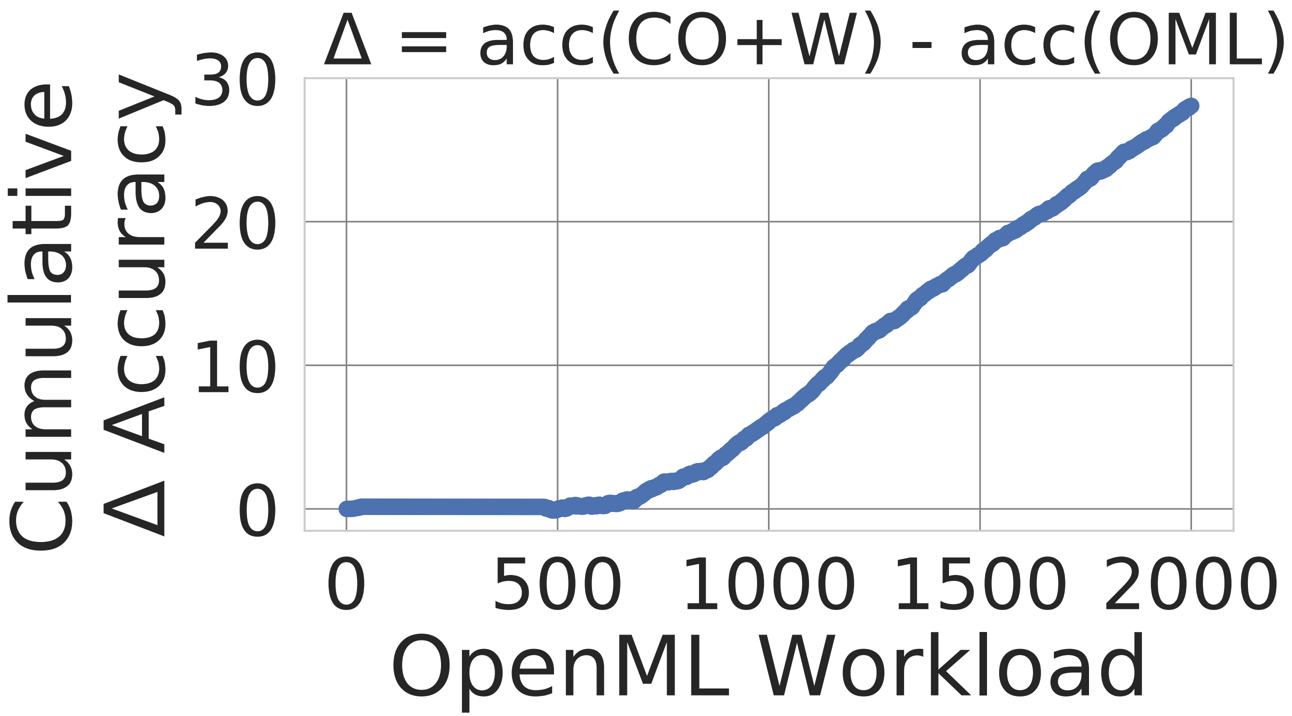
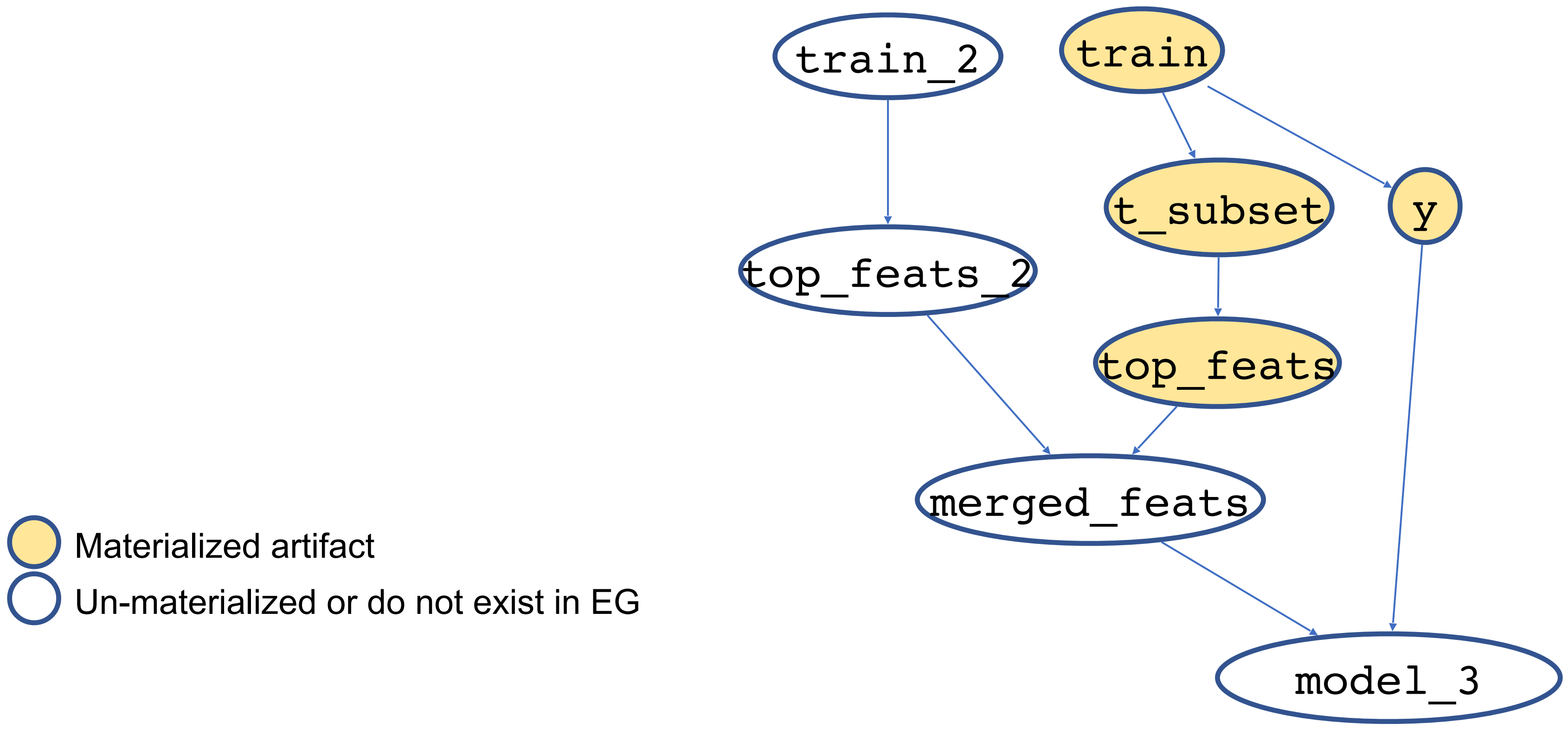
Impact of Model Warmstarting on Accuracy



Reuse Algorithm

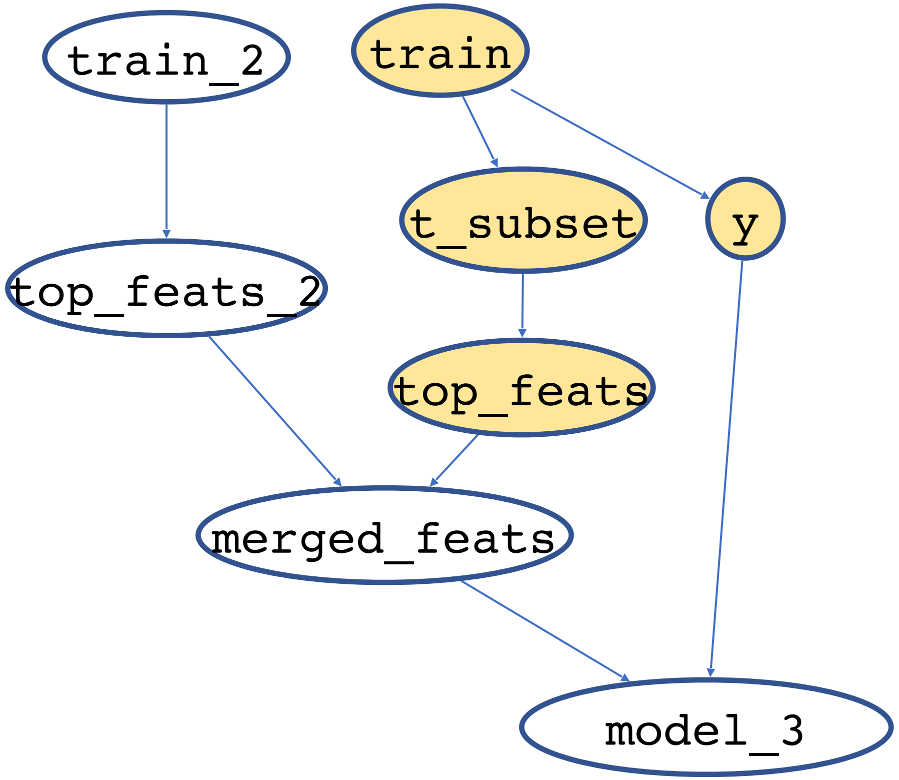
A linear-time algorithm to compute optimal execution plan with a ***forward and backward pass*** on the workload DAG



Reuse Algorithm (Forward-pass)

Forward-pass

1. Traverse from the source
2. Accumulate run-times
3. For every materialized node compare the **accumulated run-time** with the **load-time**



Materialized artifact

Un-materialized or do not exist in EG

Artifacts to execute

Artifacts to load

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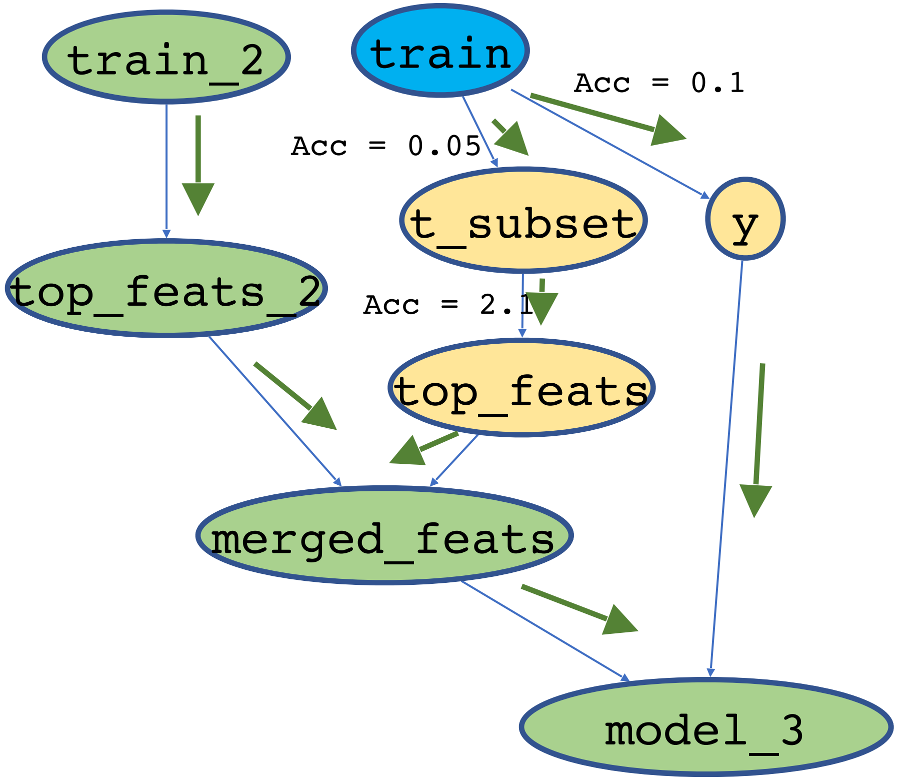

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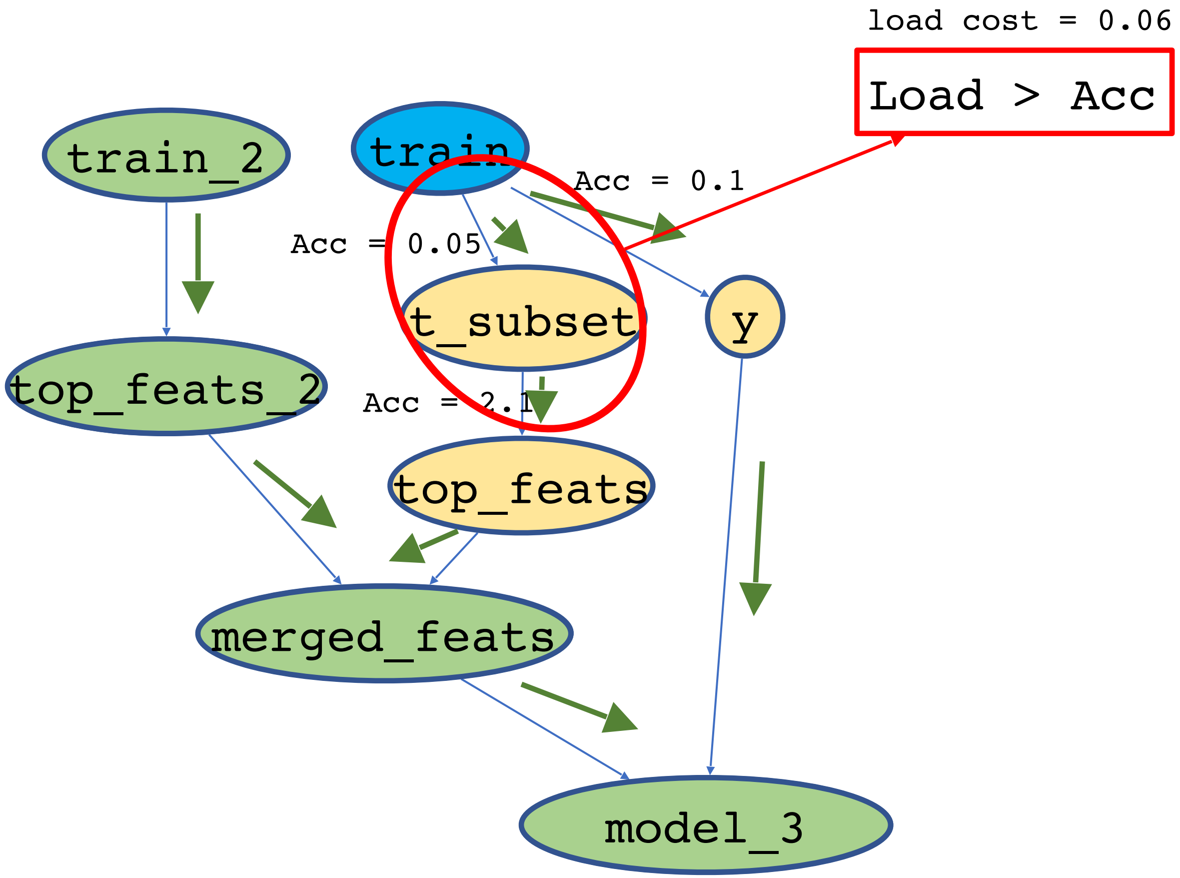

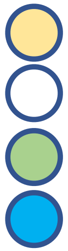

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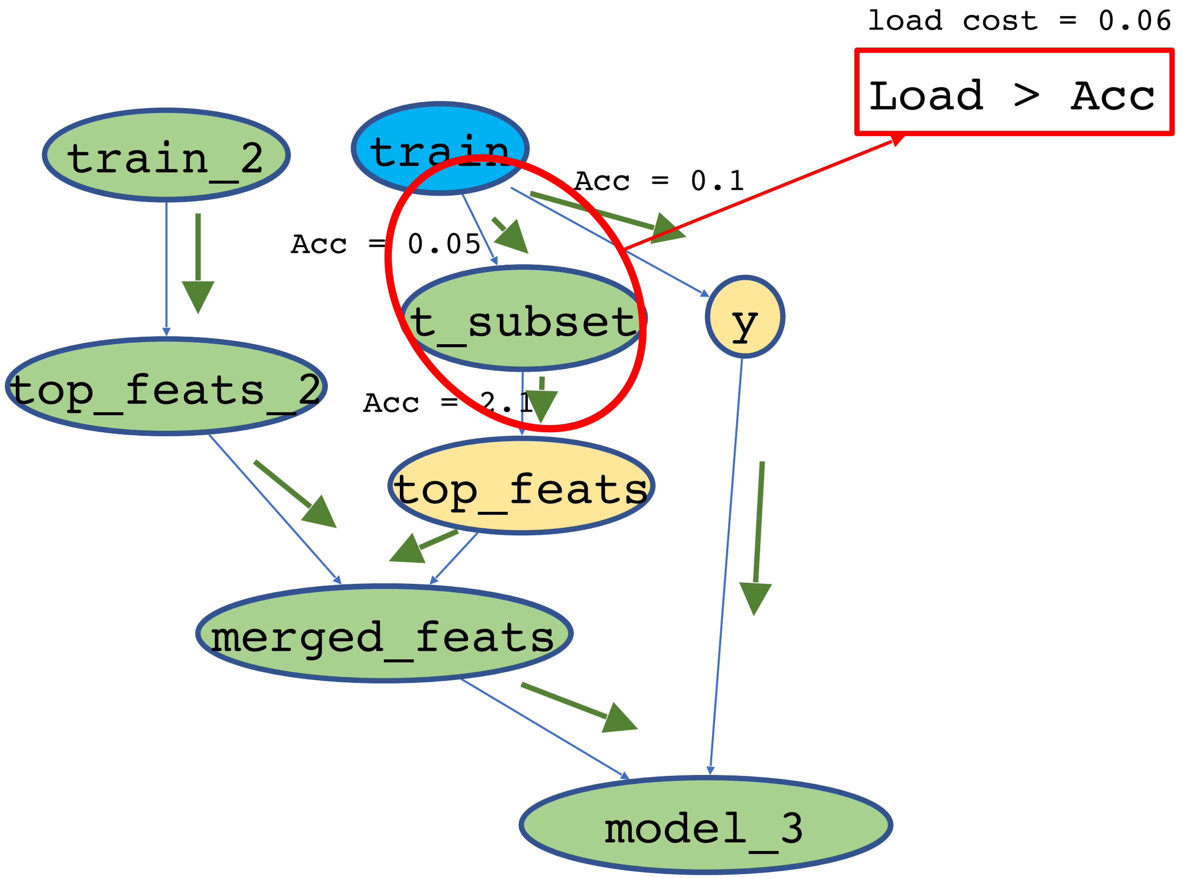

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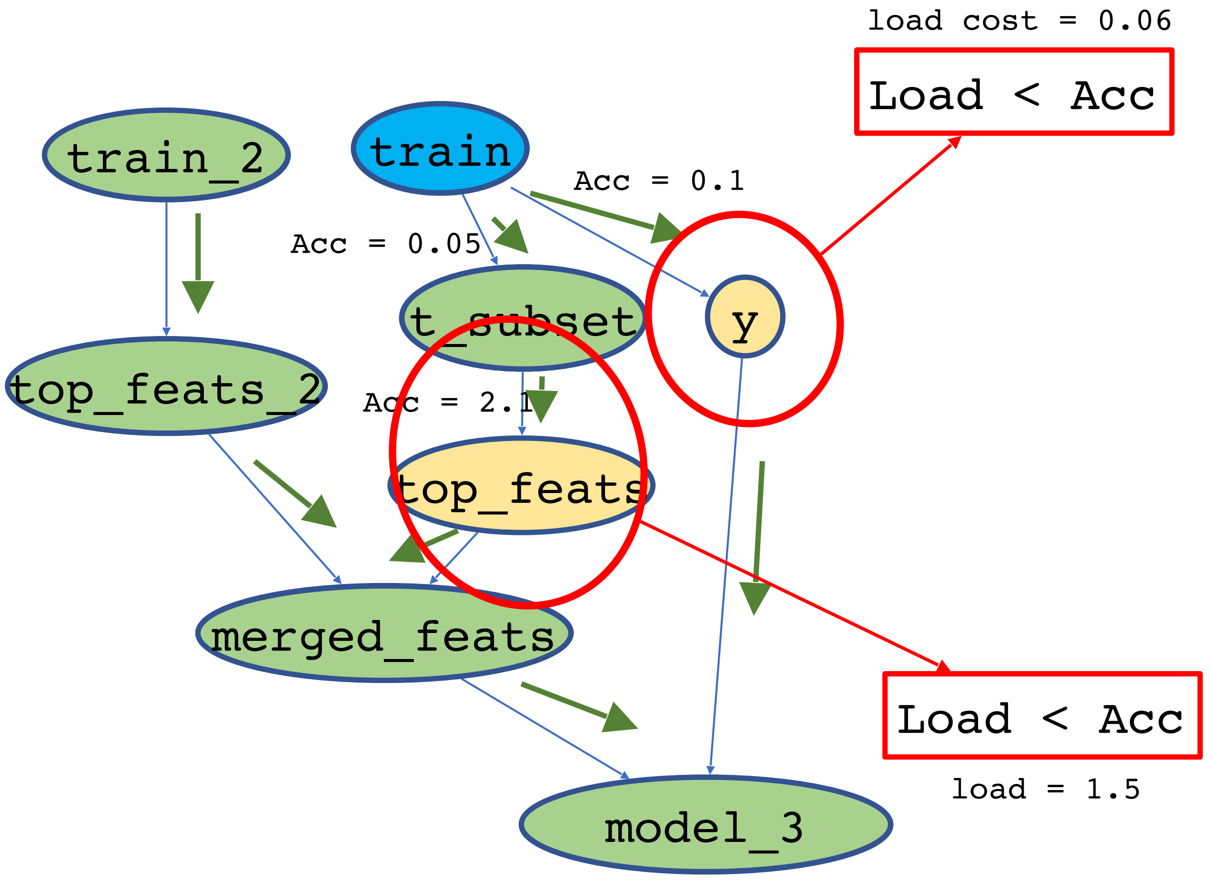

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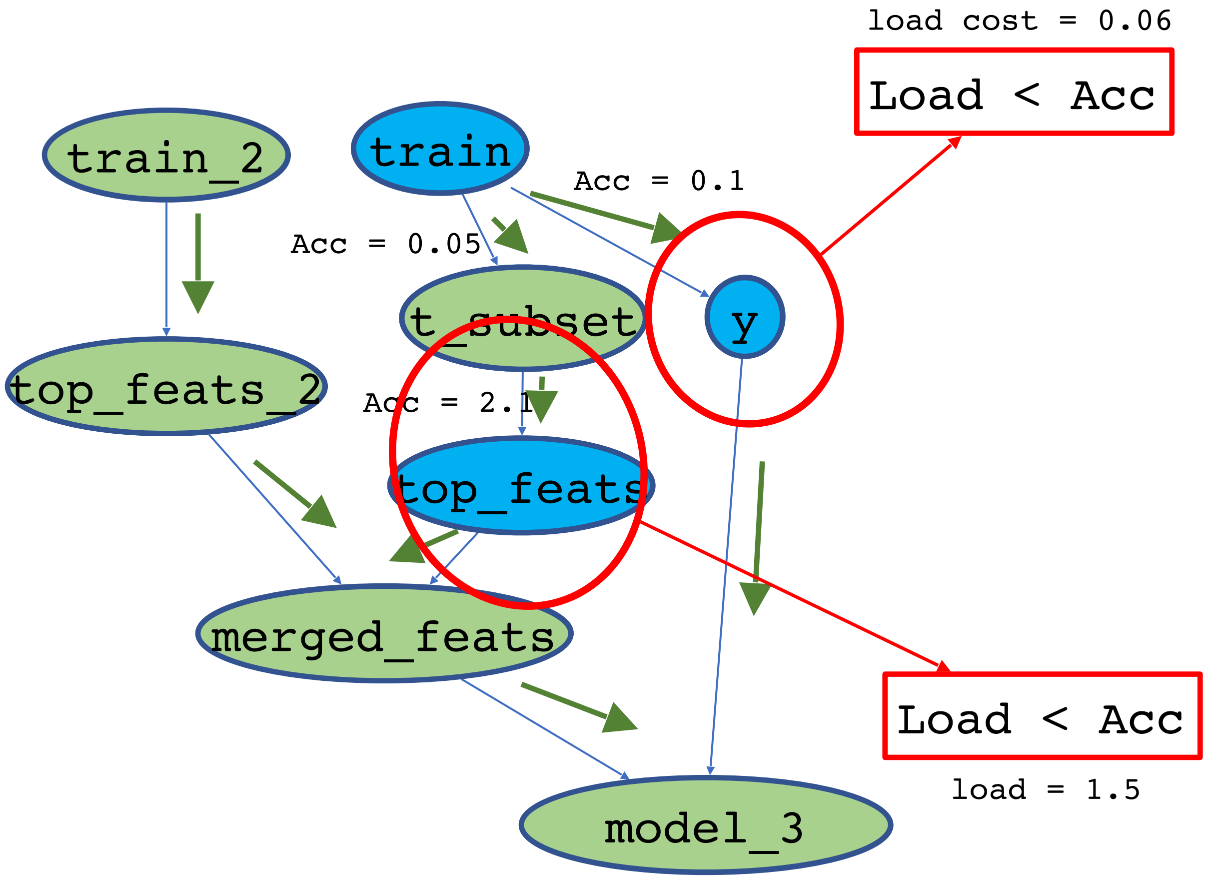

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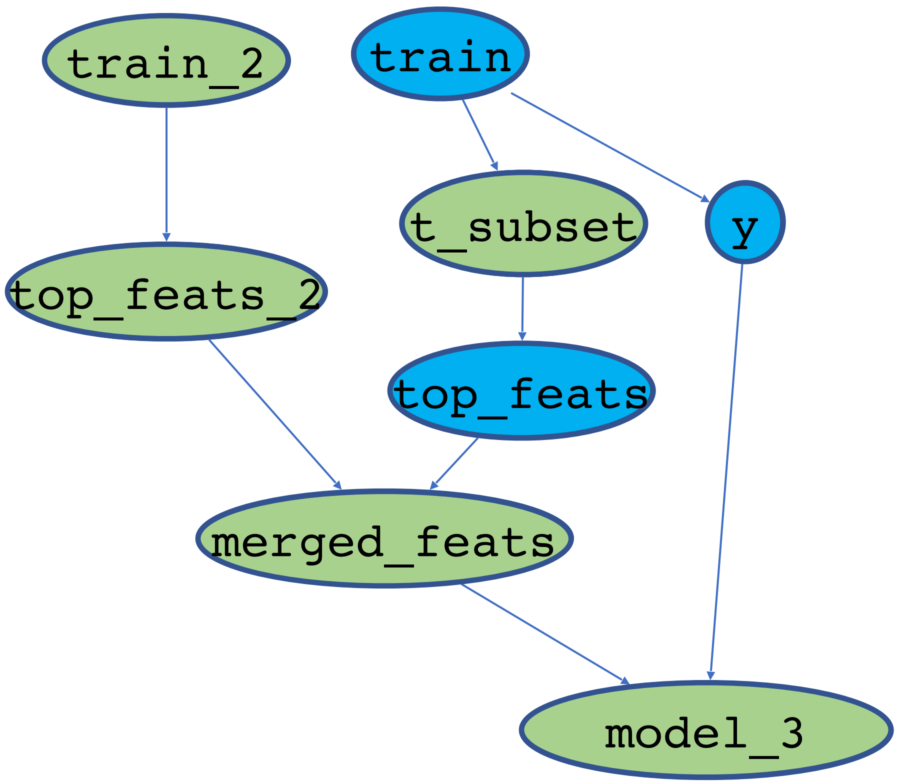

Materialized artifact
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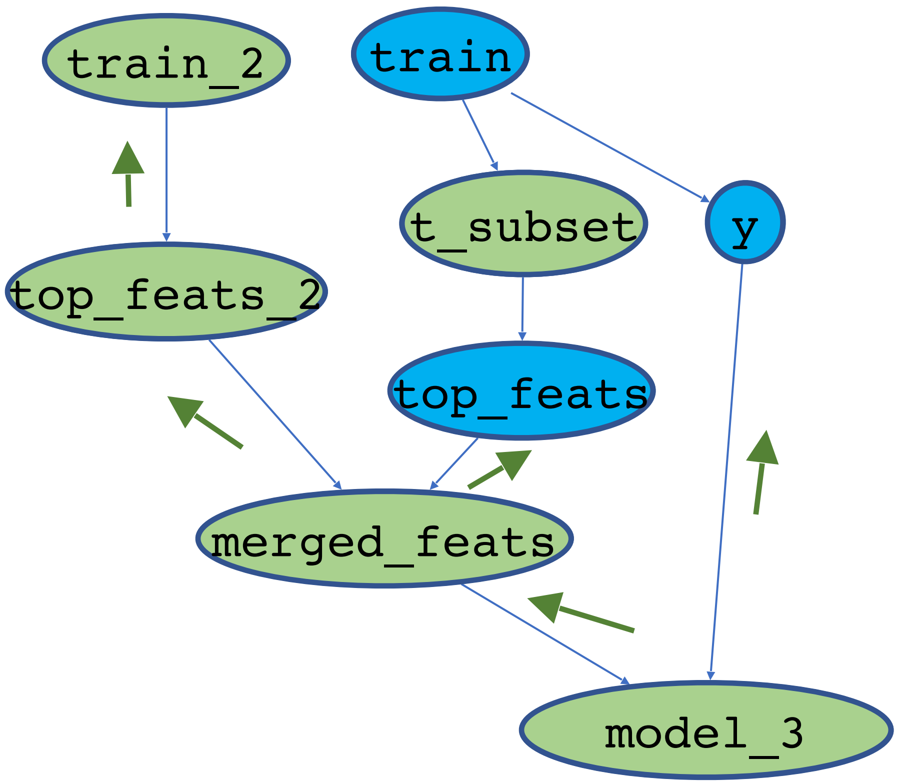
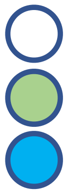
Reuse Algorithm (Backward-pass)

Backward-pass
1. Traverse backward from the terminal 2. For every **loaded** artifact, stop the traversal of its parents 3. **Prune** artifacts that are not visited





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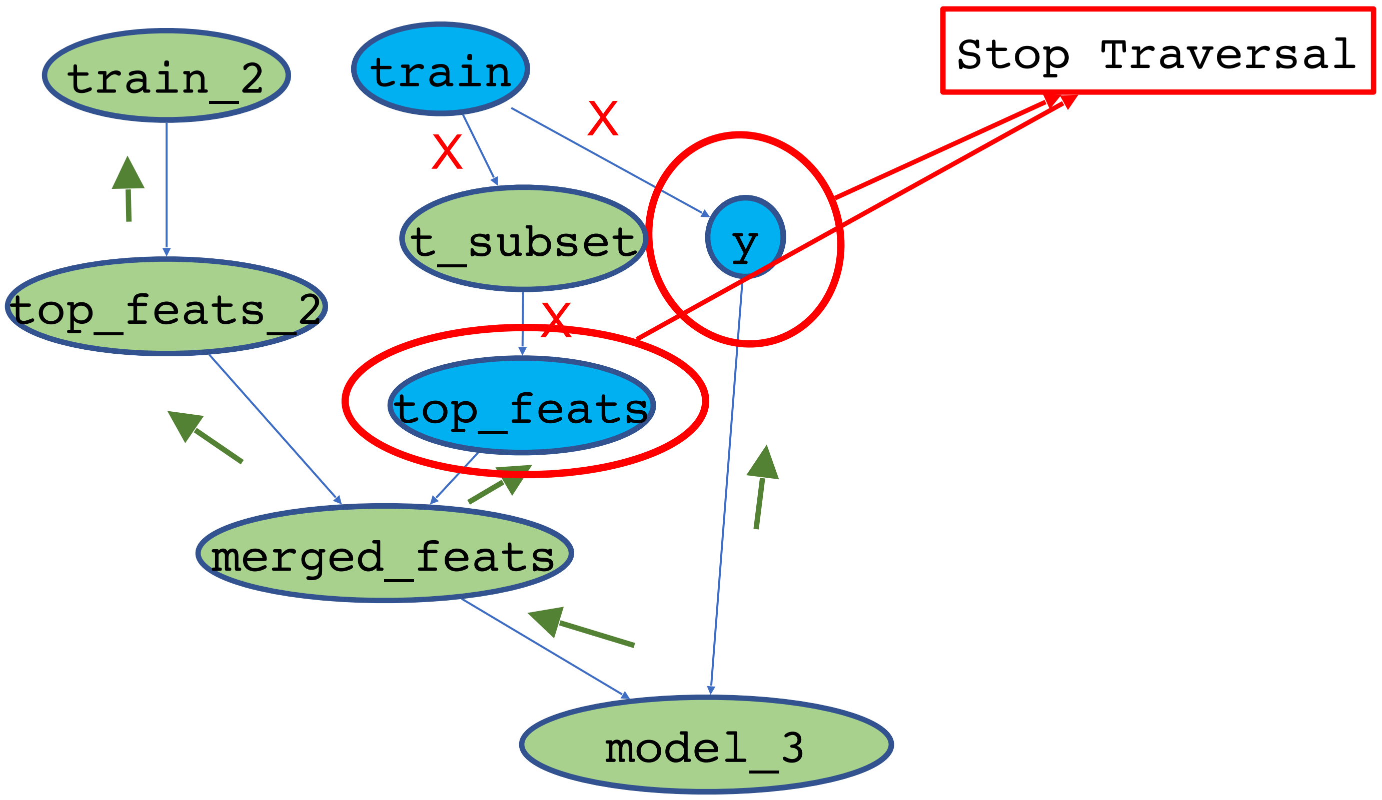

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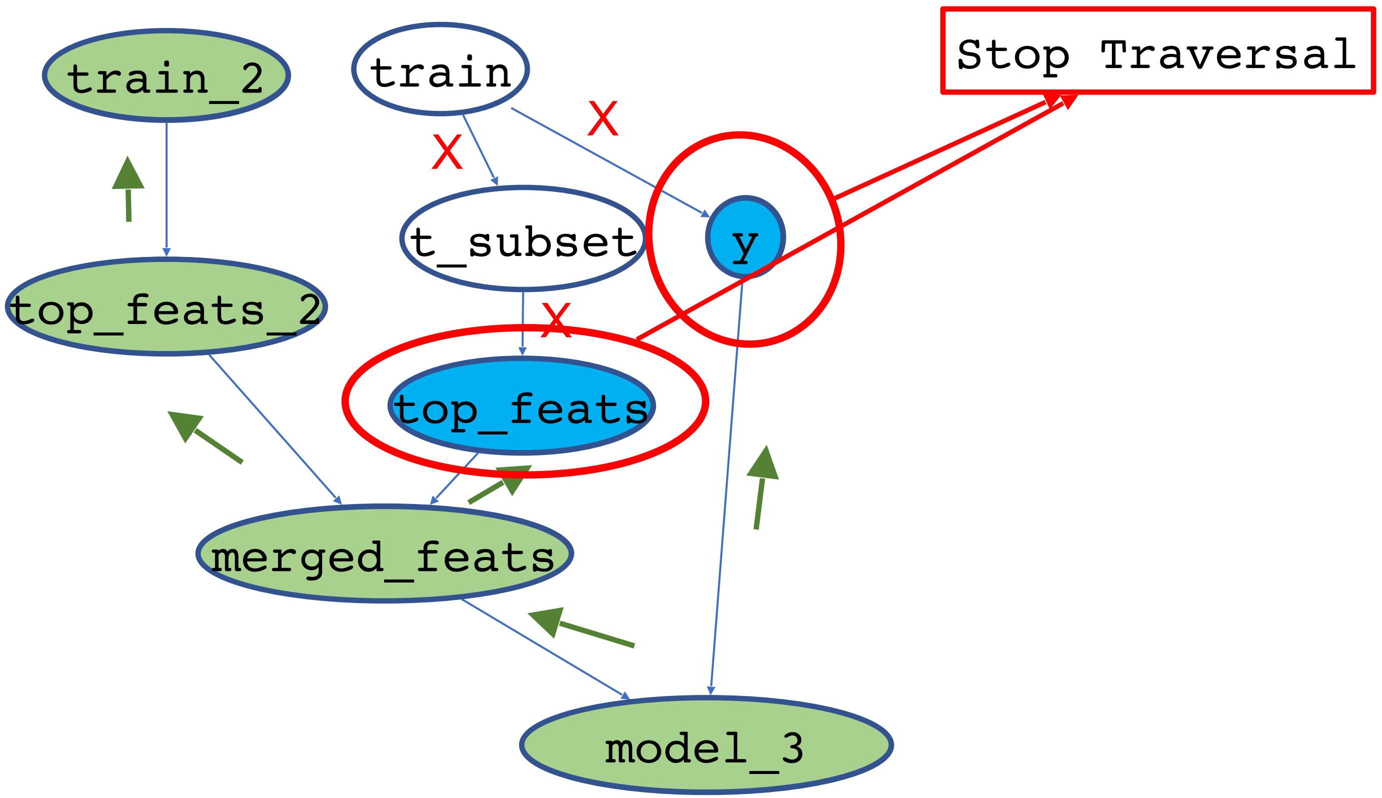

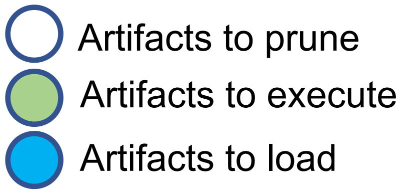

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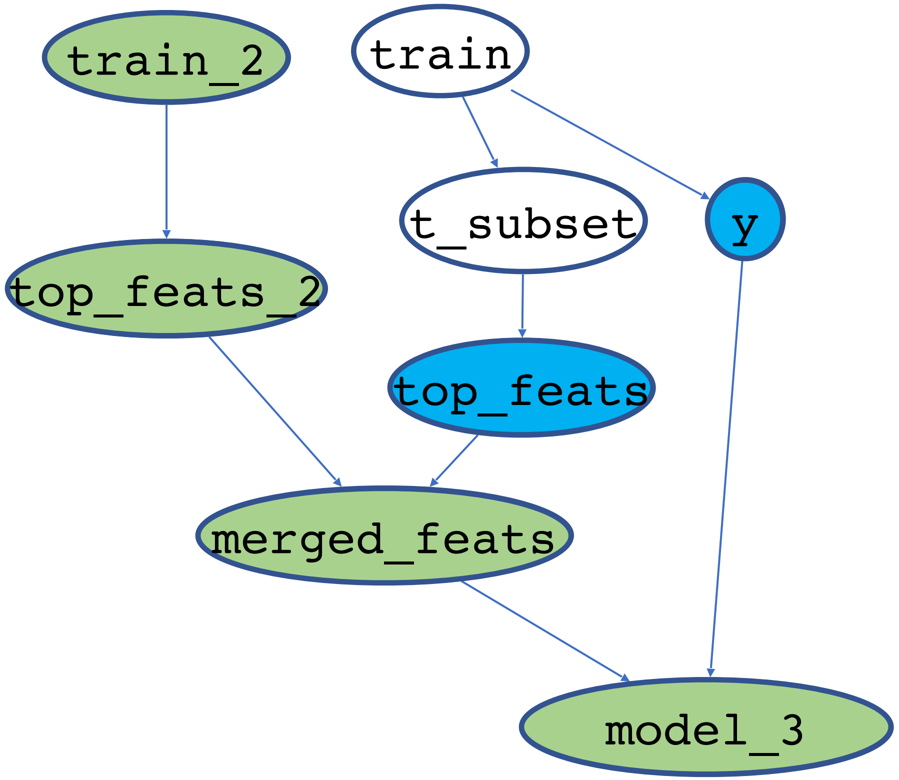

Artifacts to prune
Artifacts to execute
Artifacts to load

Storage-aware Materialization

- Many **duplicated** columns in intermediate data artifacts
- Apply column deduplication strategy

```
train = pd.read_csv('train.csv') #
[ad_desc,ts,u_id,price,y]
ad_desc = train['ad_desc‘]
t_subset = train[['ts','u_id','price‘]]
y = train['y']
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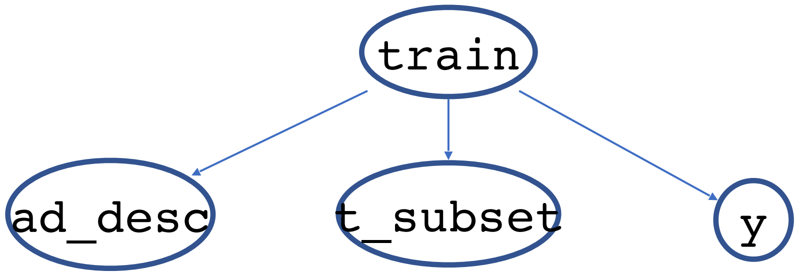

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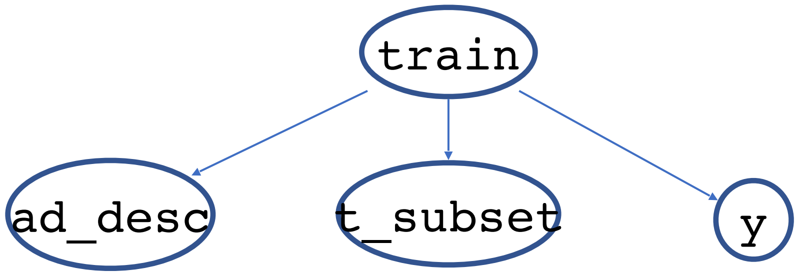

Storage-aware Materialization
while budget is not exhausted:
1. run materialization algorithm
2. deduplicate the materialized artifacts
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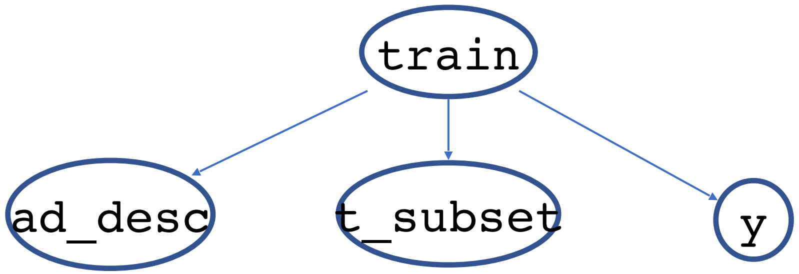

Storage-aware Materialization
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Improves Storage utilization and Run-time

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