

Machine Learning Pipelines

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Things to remember

- **Due Monday:** [Features and Pipeline v0 assignment](#)

Finishing Up Temporal Validation

Parameters

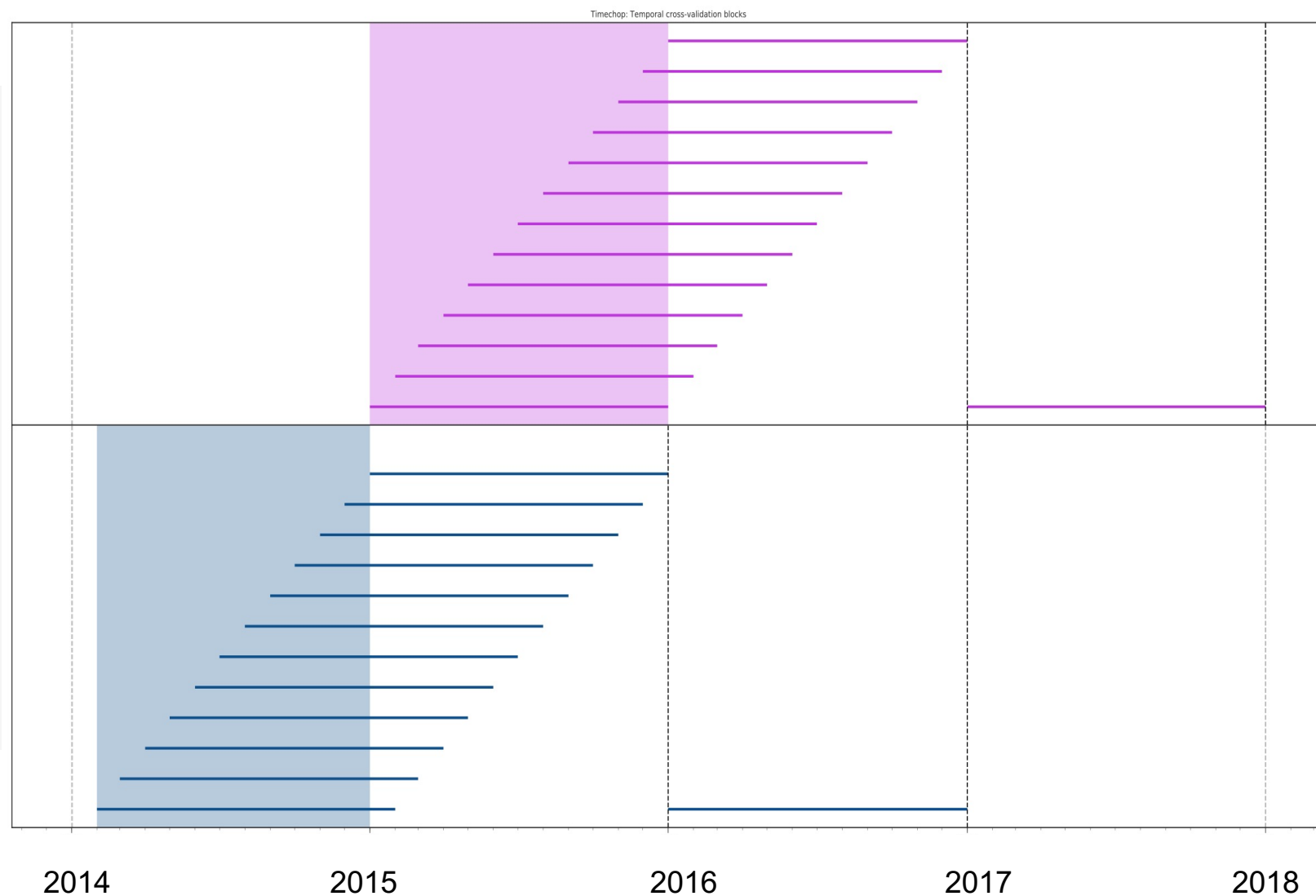
- How far back to go when training models? (max training history)
 - To the beginning of time (expanding training window)?
 - Fixed history (rolling training window)?
 - Something else?
 - How far back do you get your features from?
- How much to move forward from train-validation pair 1 to train-validation pair 2?
 - A day?
 - A month?
 - Something else?

Other considerations

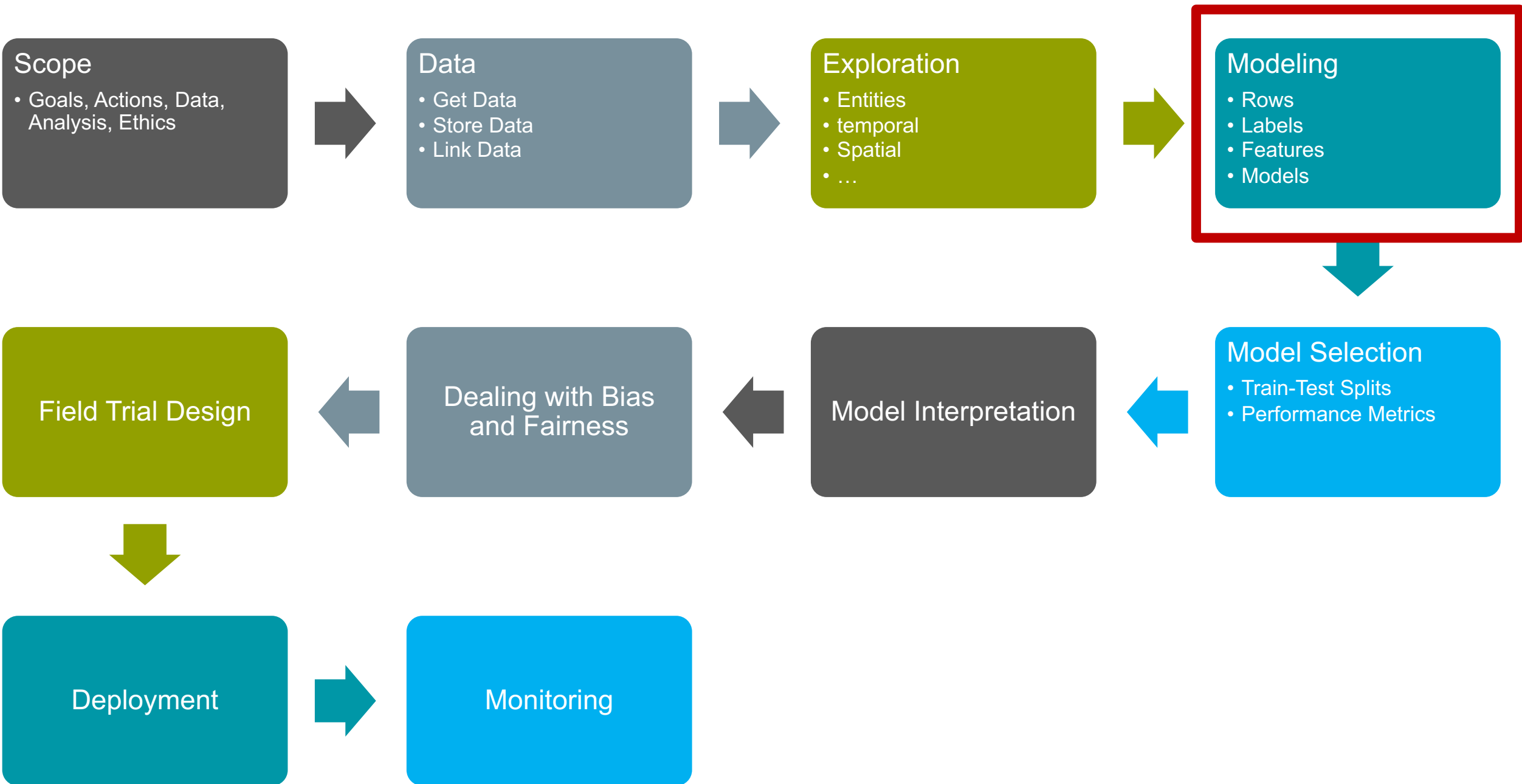
- If making repeated predictions about the same entity at different times, how often should an entity be repeated in the training data?
 - In an event-based deployment setup?
 - In a “take action at regular-ish intervals” deployment?
- What about in the validation set?

Temporal configuration parameters

```
temporal_config:  
  feature_start_time: '2014-01-01'  
  feature_end_time: '2018-01-01'  
  label_start_time: '2014-01-02'  
  label_end_time: '2018-01-01'  
  
  model_update_frequency: '1y'  
  training_label_timespans: ['1y']  
  training_as_of_date_frequencies: '1month'  
  
  test_durations: '0d'  
  test_label_timespans: ['1y']  
  test_as_of_date_frequencies: '1month'  
  
  max_training_histories: '1y'
```



Machine Learning Pipelines



Things we will cover

- What is an ML Pipeline?
- Why should we build ML pipelines?
- What components should it have?
- Best Practices
- Good Examples

What is an ML Pipeline?

- Supports end-to-end workflow for an ML project/system
- Modular
- Reconfigurable

Why build a pipeline?

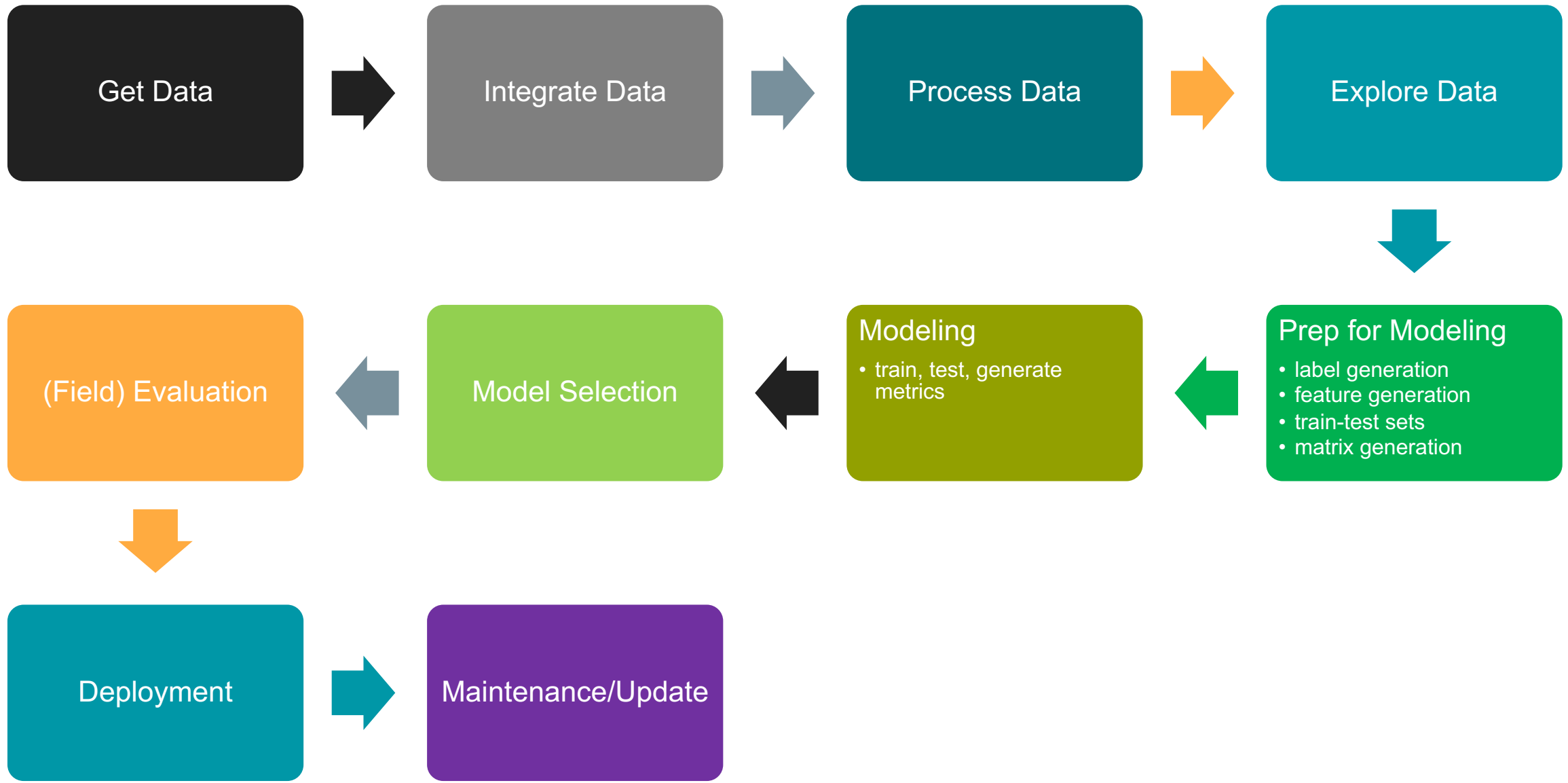
- Reusable across projects
- Test new ideas, components, hypothesis easily
- Reduce bugs/errors
- Allows reproducibility of analysis and results

What makes a pipeline?

- Inputs
- Components
- (Intermediate and final) outputs

Pipeline Flow & Components

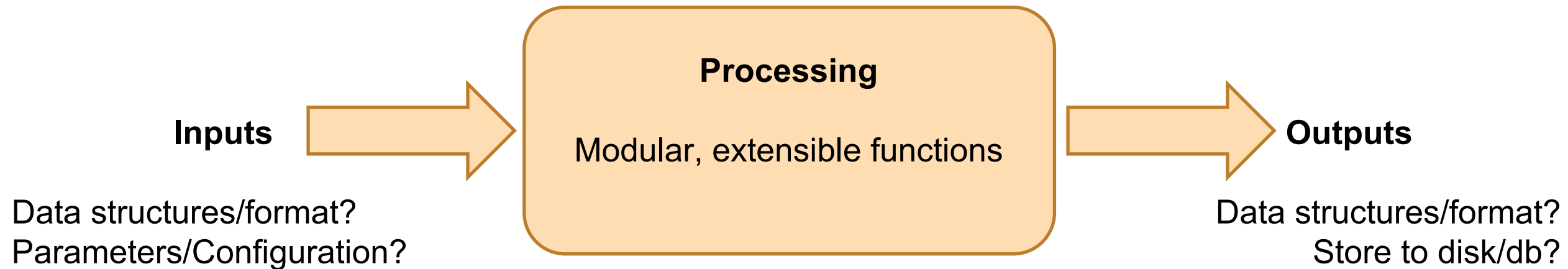
Pipeline Flow



What components does a pipeline have?

- Read/Load Data (from csv, db, api)
- Integrate Data (dedupe, link)
- Process Data (cleaning)
- Explore Data (descriptive stats, correlations, outliers, over time, clustering)
- Modeling Prep
 - Create training and test sets
 - Missing values (fill/impute, create dummy)
 - Transformations (scale/normalize, log, square, root)
 - Feature Generation
 - Label Generation
 - Define metric(s)
- Modeling
 - Build model(s) on training sets
 - Apply model(s) on test sets
 - Calculate metric(s)
- Model Selection
- Field Trial
- Deploy
- Maintain

Things to keep in mind about each component



Components: Data Acquisition & Integration

- Get Data
 - API, CSV, Database
- Store Data
 - Database
- Integrate Data
 - Record Linkage

Components: Explore and Prepare data

- Data Exploration
 - Distributions
 - Missing Values
 - Correlations
 - Other Patterns
- Pre-Processing
 - Leakage
 - Deal with Missing values
 - Scaling
 - Data errors

Components: Feature Creation

- Data comes with fields or columns (if it's even structured), not features
- Common Features
 - Discretization
 - Transformations
 - Interactions/Conjunctions
 - Disaggregation
 - Aggregations
 - Temporal
 - Spatial
- How are you handling imputation of missing values?

Components: Method Selection

- Select pool of methods applicable for task
- For loop over a large number of methods
 - For loop over parameters

Components: Validation

- Using historical data
 - Methodology
 - Metric
- Field Experiment
 - Methodology
 - Metric

Deployment

- Model monitoring
- Re-training
 - How often?
 - Re-select methods?
- Scoring

What types of variations do you want to test using your pipeline?

- Different models
- Model parameters
- Different Labels/Outcomes
- Different Deployment Settings
- Different Feature (Groups)
- Different Metrics

Best Practices

- Draw a diagram of the pipeline:
 - What function runs each step? What are the inputs? What are the outputs?
- Config files (yaml, json, py)
- Make each step modular and extensible so it can easily be re-used
- Build a **simple**, end-to-end version first, then add more functionality
- Think about how you'll store outputs:
 - Store models as pickles
 - Store predictions in databases
 - Store evaluation metrics in databases
 - Database schema to store everything in

- Timesplitter
 - Input: start time, end time, update time, prediction time
 - Output: pairs of <train start time, train end time, test start time, test end time>
- CohortCreator
 - Input: timesplitter output, cohort definition,[entity_ids, as of date]
 - Output: cohort matrix <entity_id, as_of_date>
- LabelCreator
 - Input: pairs <entity_id, as_of_date>, label definition
 - Output: matrix <entity_id, as_of_date, label>
- FeatureCreator
 - Input: pairs <entity_id, as_of_date>, feature definition(s)
 - Output: matrix <entity_id, as_of_date, feature(s)>
- ModelTrainer
 - Input: model definition, matrix, feature columns, label column
 - Output: model object (stored), model definition
- ModelScorer
 - Input: model object, matrix, feature columns
 - prediction scores
- Evaluator
 - Prediction scores, label column, metric(s)

Progression

1. Determine Input/outputs for each component
2. Example of code for each component
3. python file that imports each component and builds a pipeline for 1 train test set, 1 model, 1 metric, etc.
4. Loop over additional variations
5. Move parameters from python file to external config file
6. SQL and python

Things to remember

- **Due Friday: Project Proposal**
- Remainder of this week:
 - Wednesday: tech session on using triage for ML pipelines
 - Time for group meetings/project work on Thursday
- Coming up next week:
 - Weekly review (before class on Tuesday)
 - Transductive Top-k Reading (for Tuesday)
 - Wednesday tech sessions: Python + SQL
 - Due Friday: Proposal peer reviews

Appendix:

Slides from Previous Tech Session

Train Examples

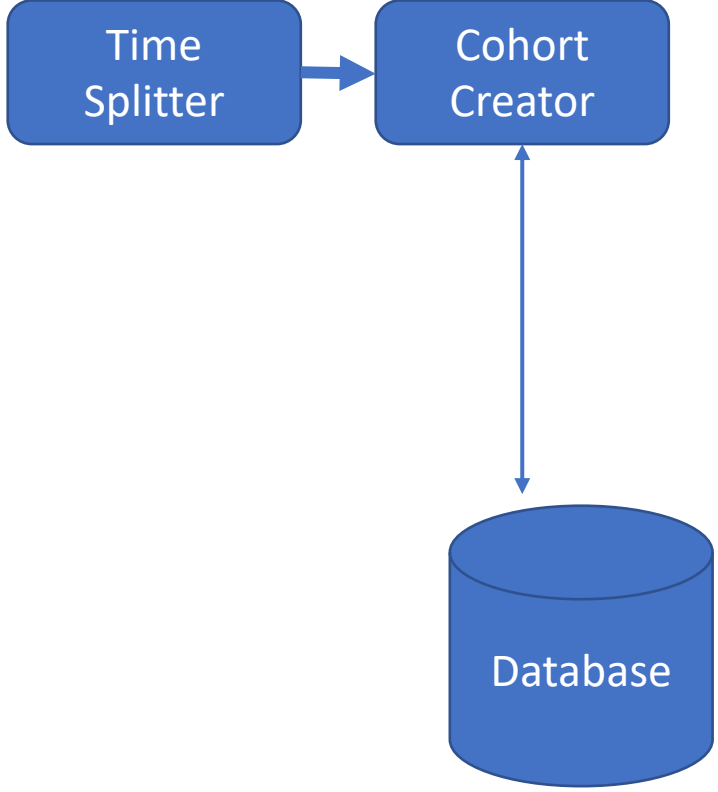
Labels

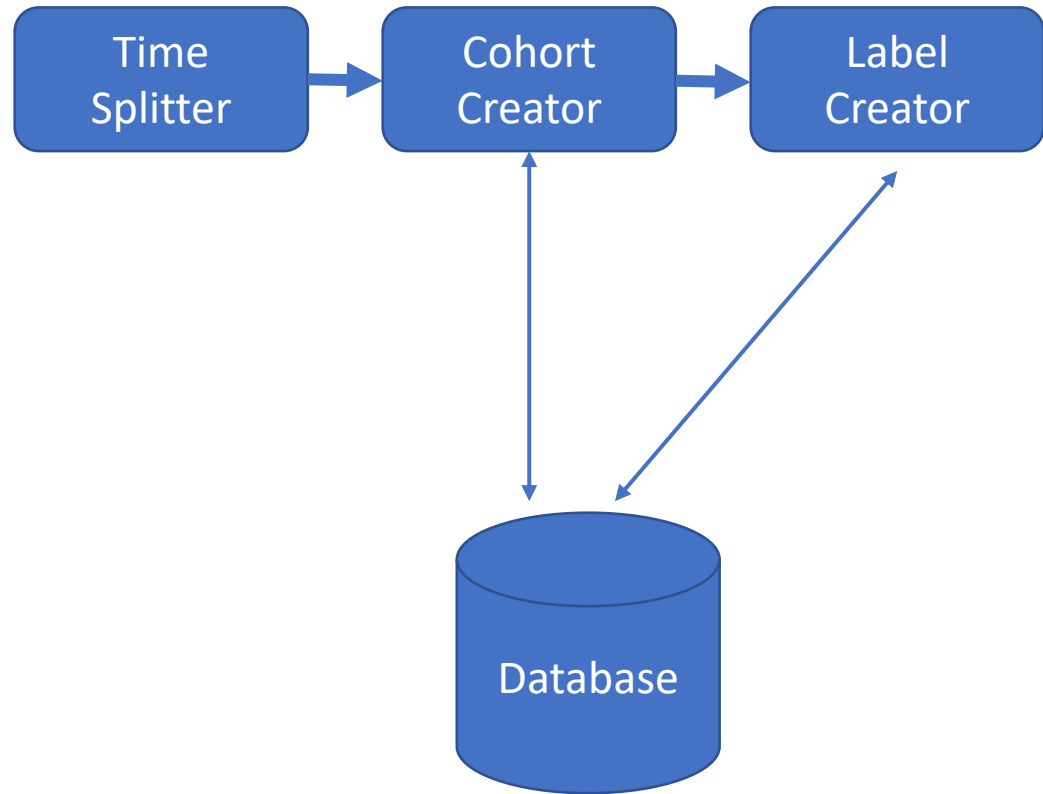
Validate Examples

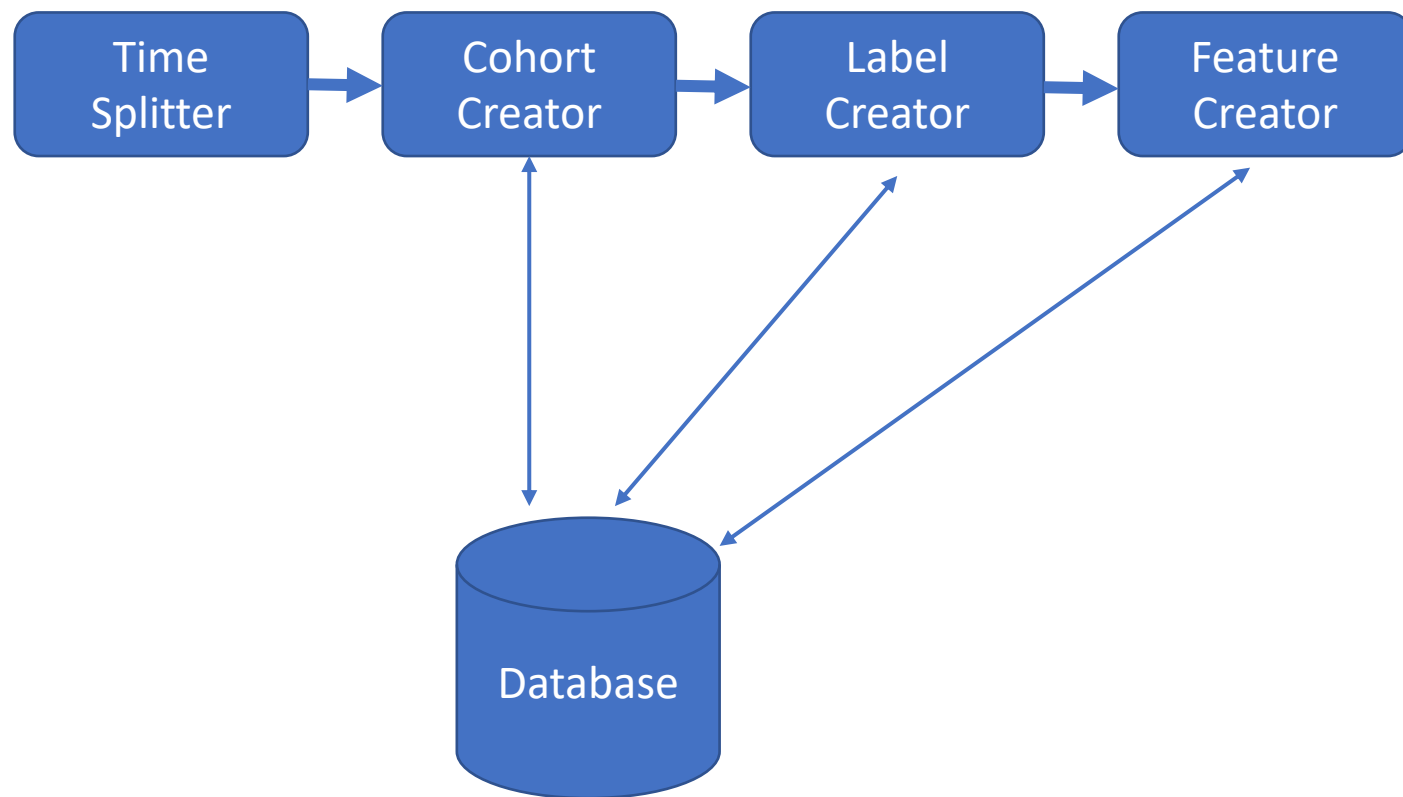
Labels

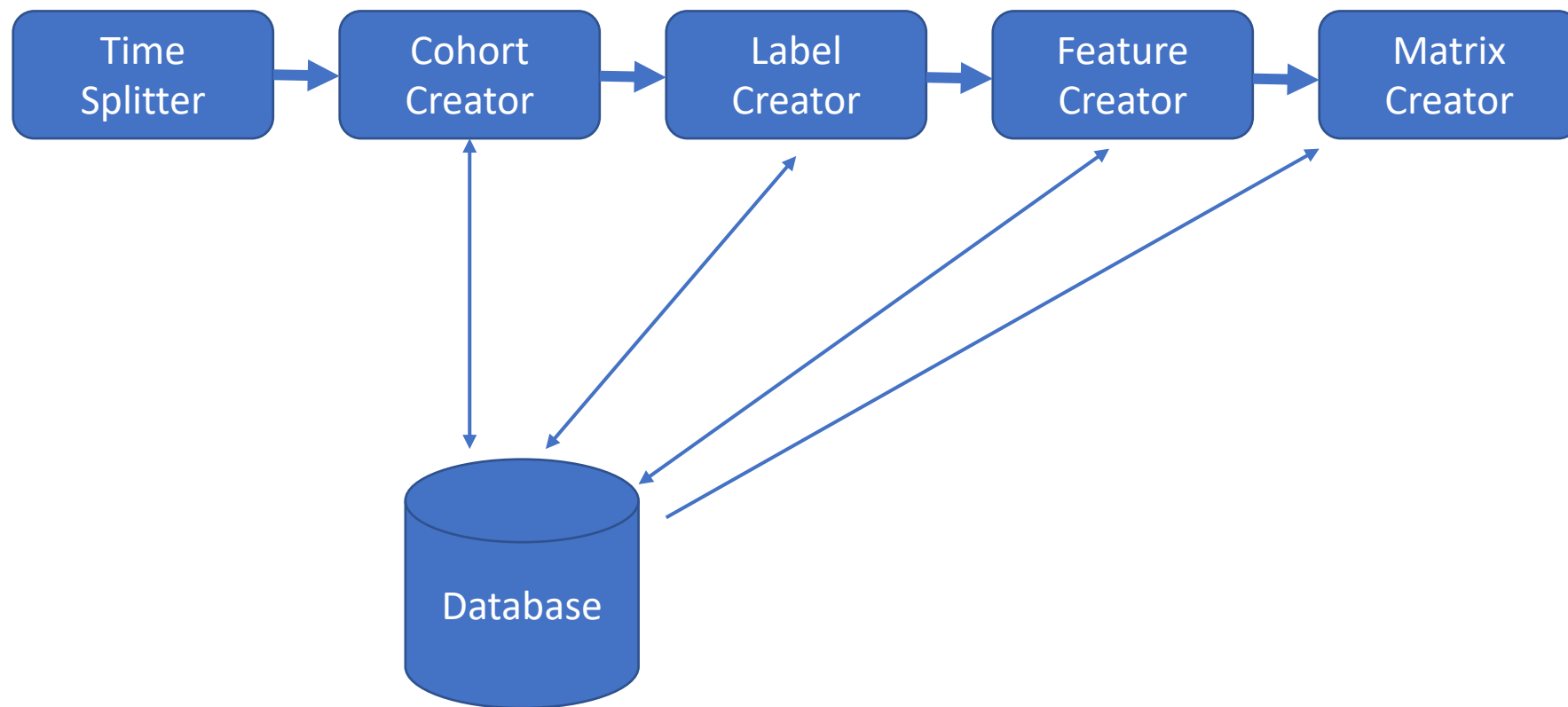


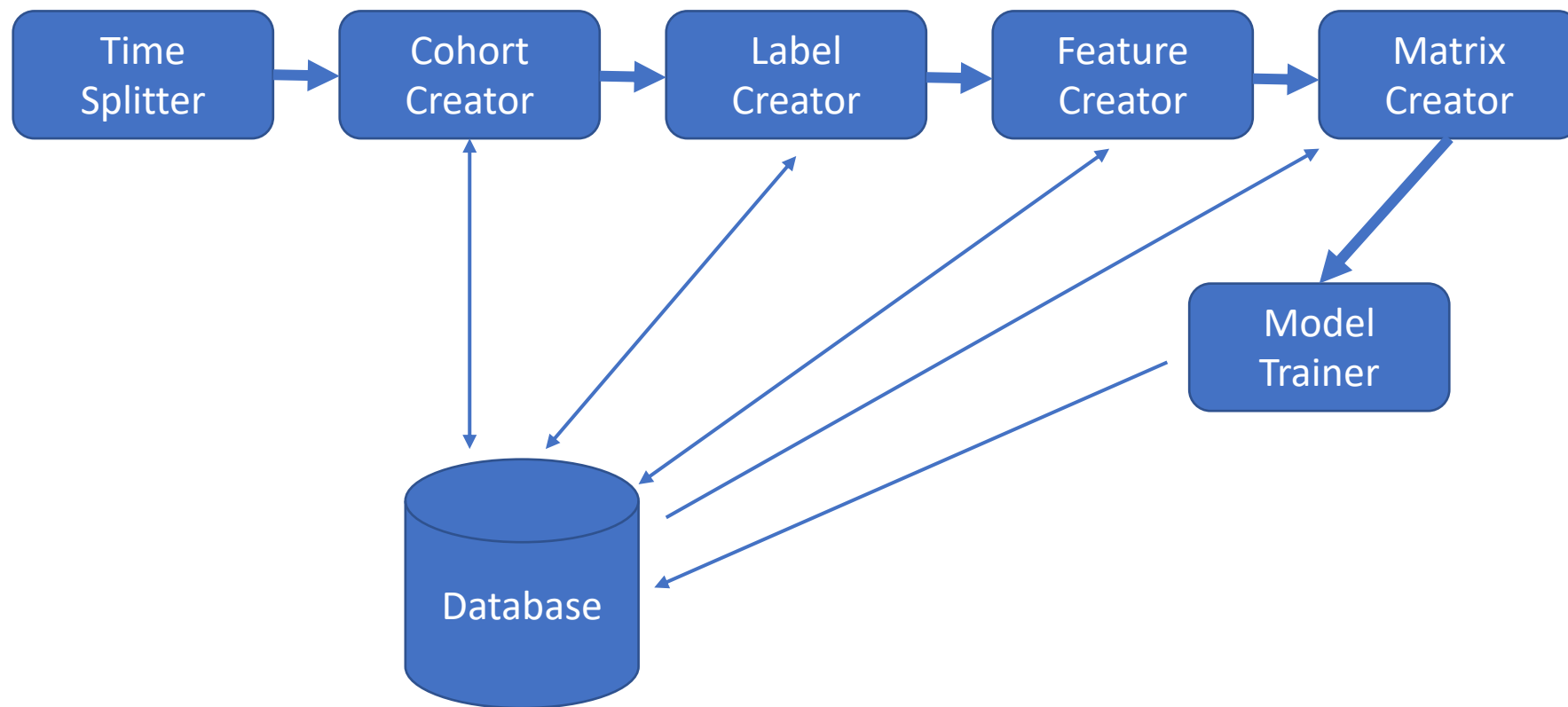
Time
Splitter

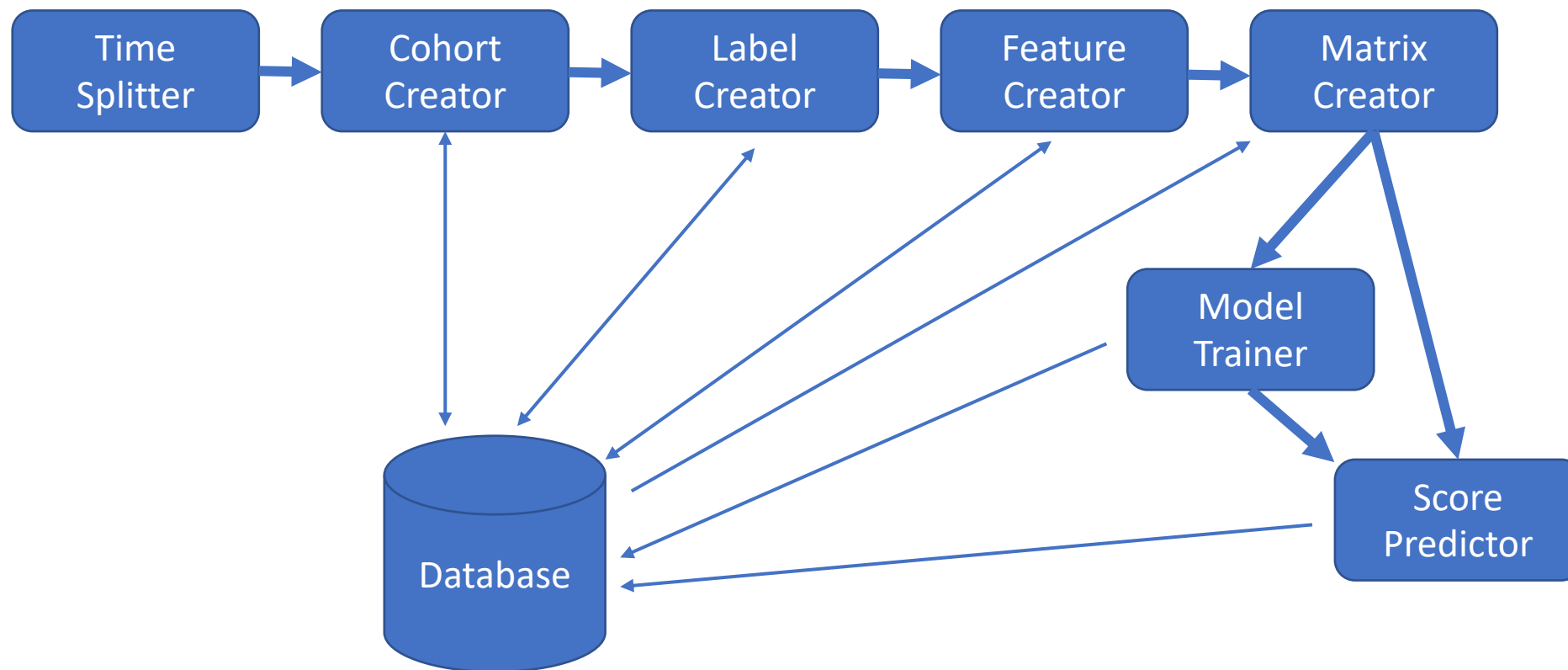


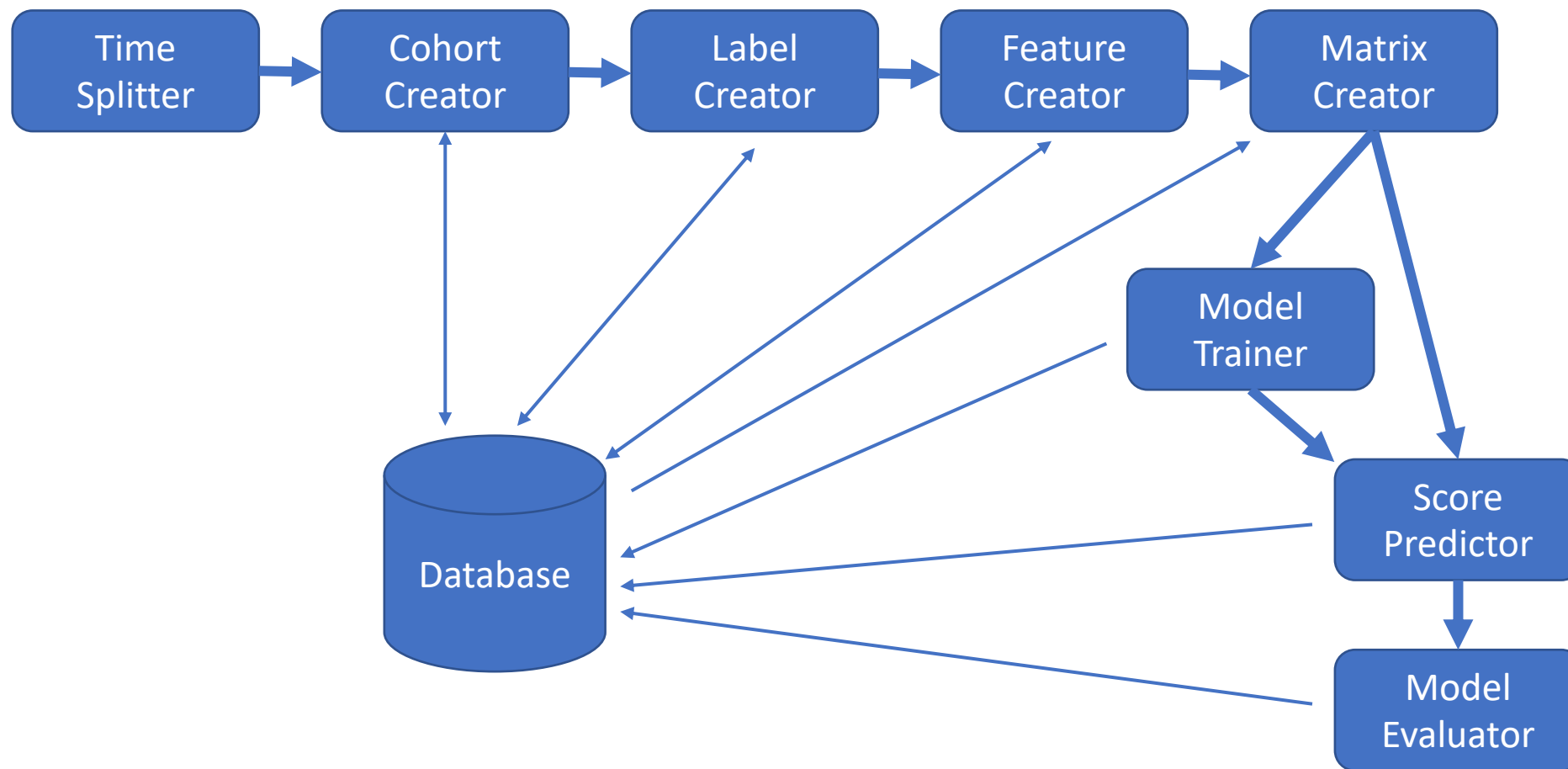


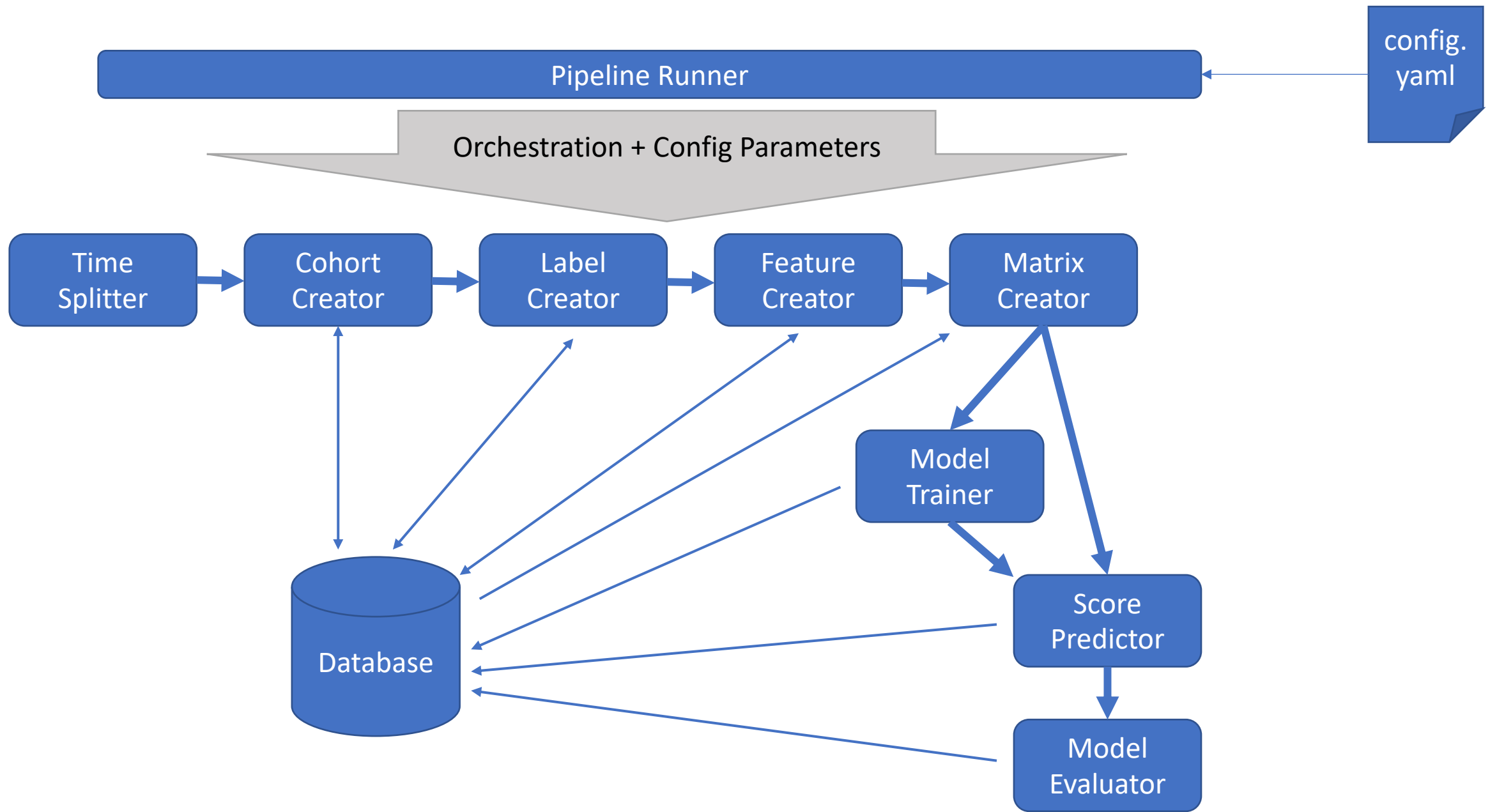


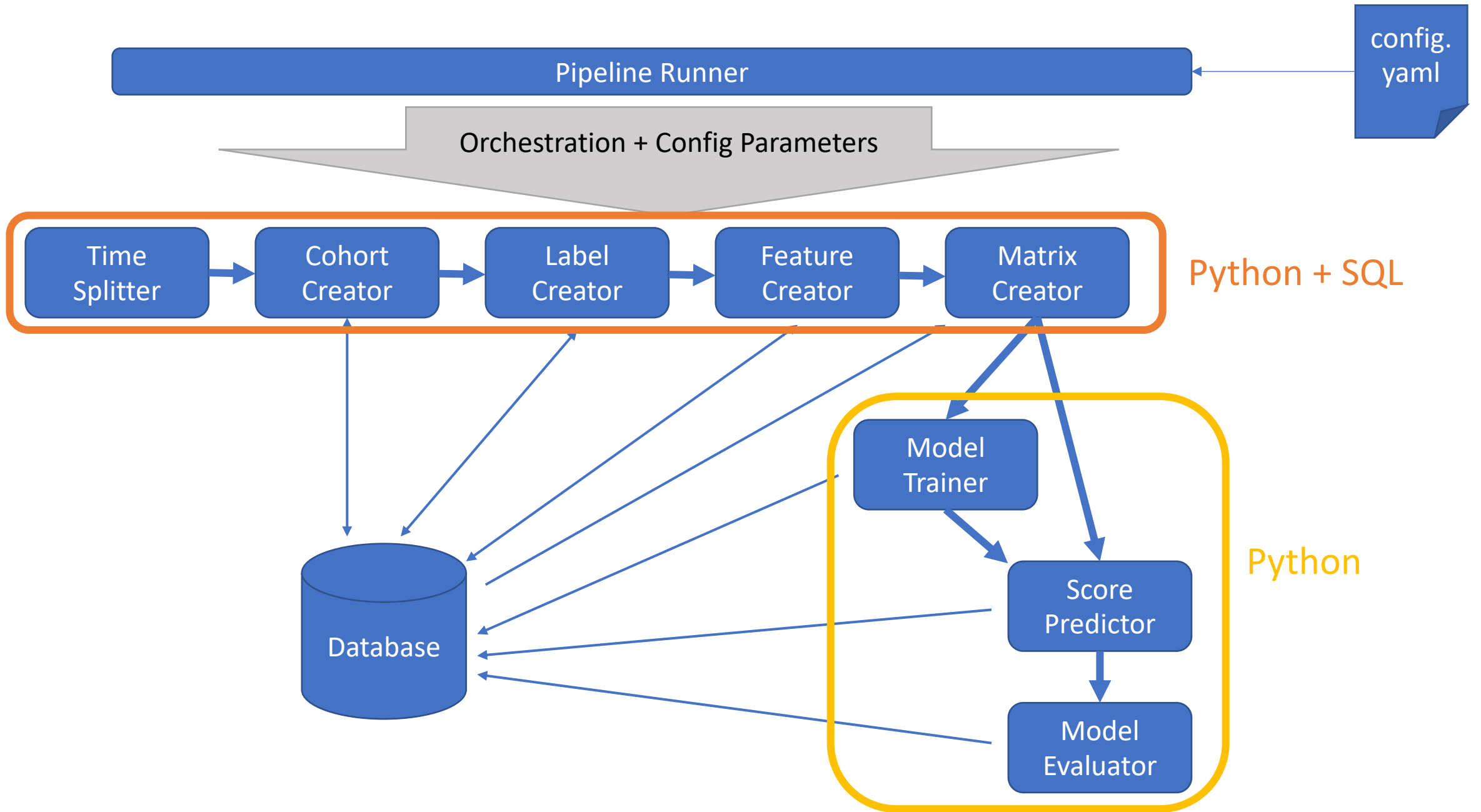


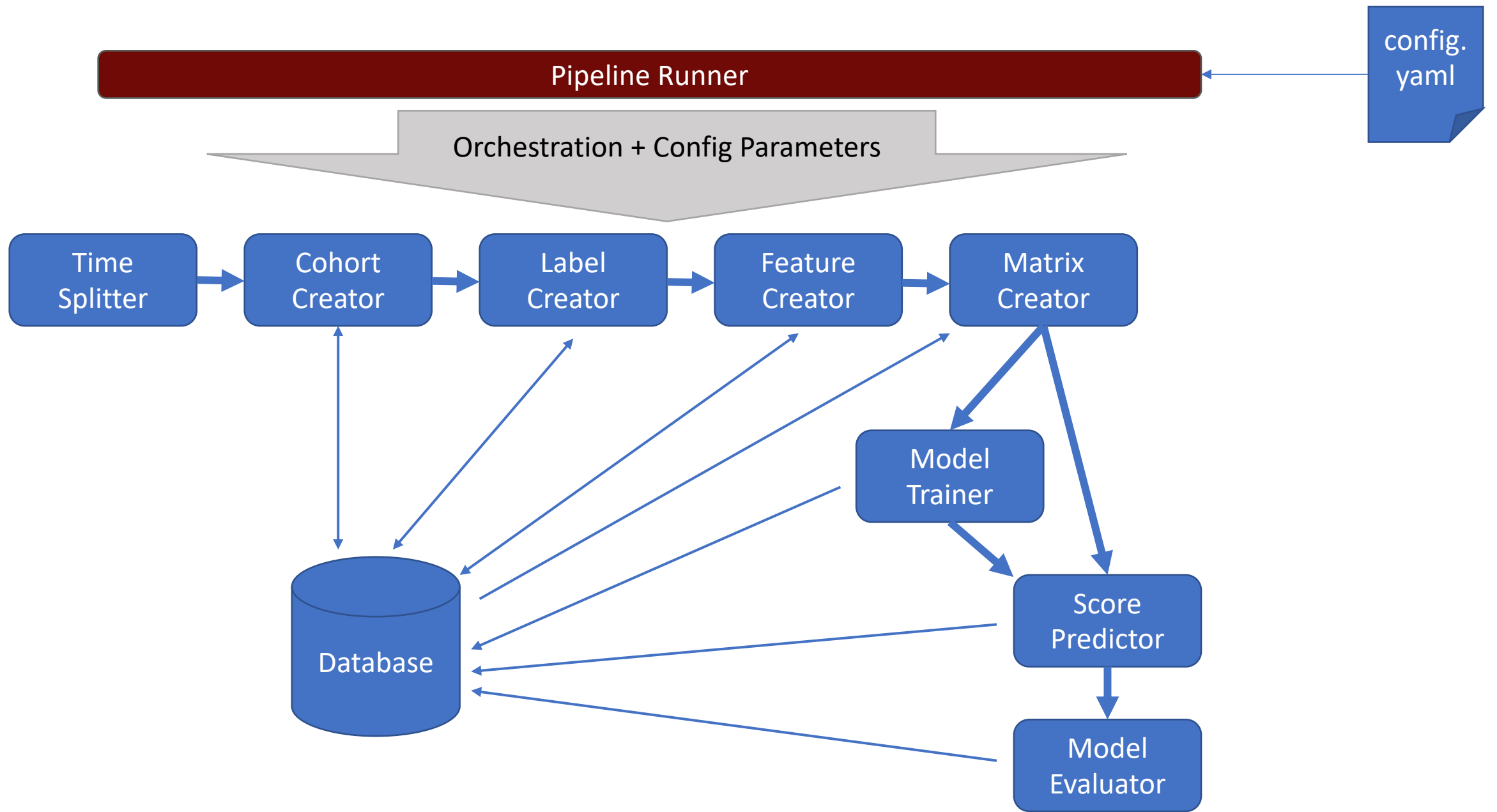






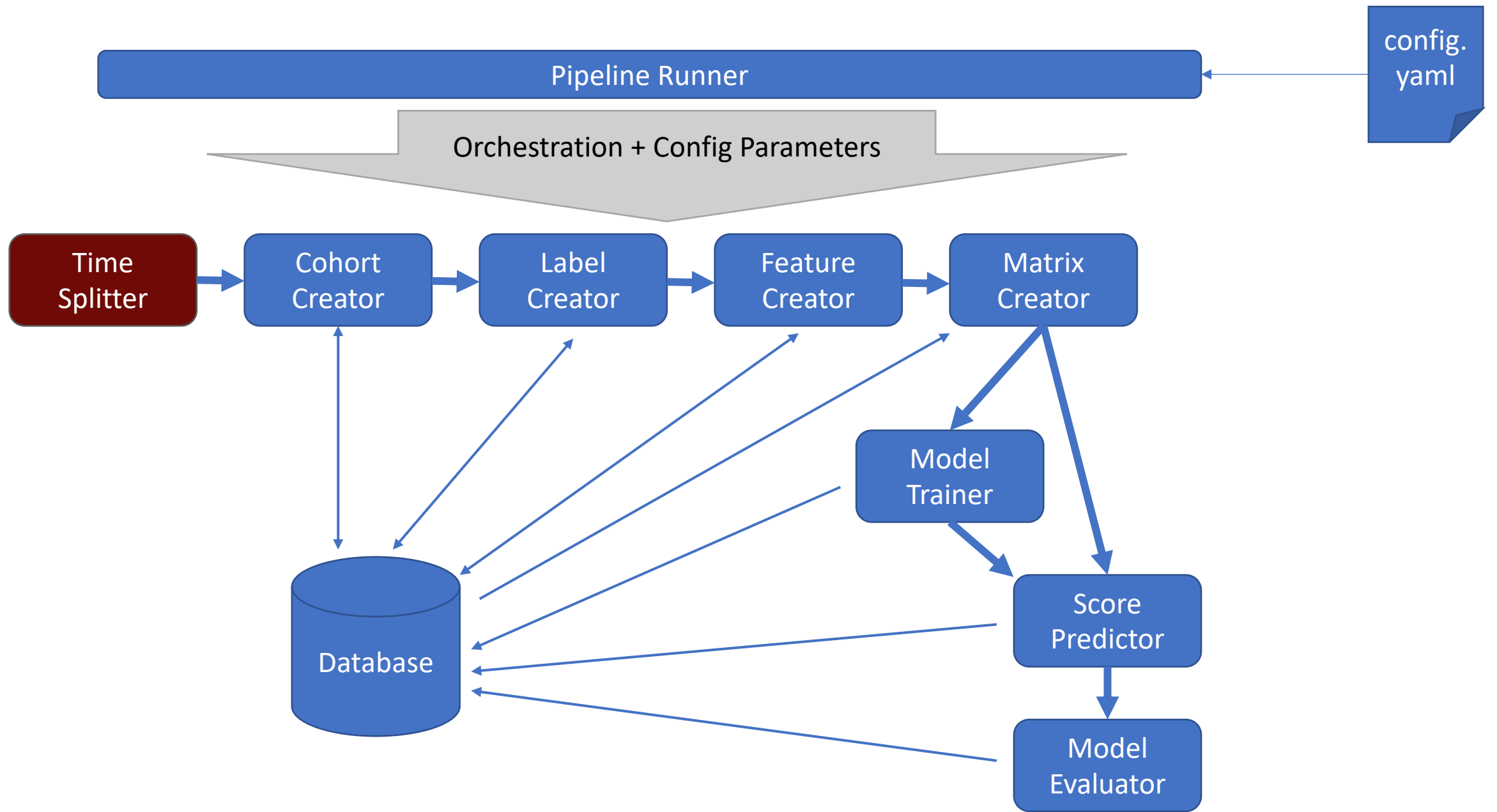






Pipeline Runner

```
1
2 from time_splitter import split_time
3 from data_prep import (
4     cohort_creator, label_generator,
5     feature_creator, matrix_maker
6 )
7 from modeling import (
8     expand_model_grid, train_model,
9     predict_scores, evaluate_model
10 )
11 import sys
12 import yaml
13
14 def run(config):
15     splits = split_time(config['temporal'])
16     cohort_table = cohort_creator(splits, config['cohort'])
17     label_table = label_generator(cohort_table, config['label'])
18     feature_table = feature_creator(cohort_table, config['features'])
19
20     for split in splits:
21         train_matrix, validate_matrix = matrix_maker(
22             split, cohort_table, label_table, feature_table
23         )
24         model_grid = expand_model_grid(config['model_grid'])
25         for model_params in model_grid:
26             model = train_model(model_params, train_matrix)
27             scores = predict_scores(model, validate_matrix)
28             metrics = evaluate_model(scores, validate_matrix)
29
30 if __name__ == '__main__':
31     config_path = sys.argv[1]
32     with open(config_path) as f:
33         config = yaml.safe_load(f)
34     run(config)
35
```



Time
Splitter

Features Data

Train Examples

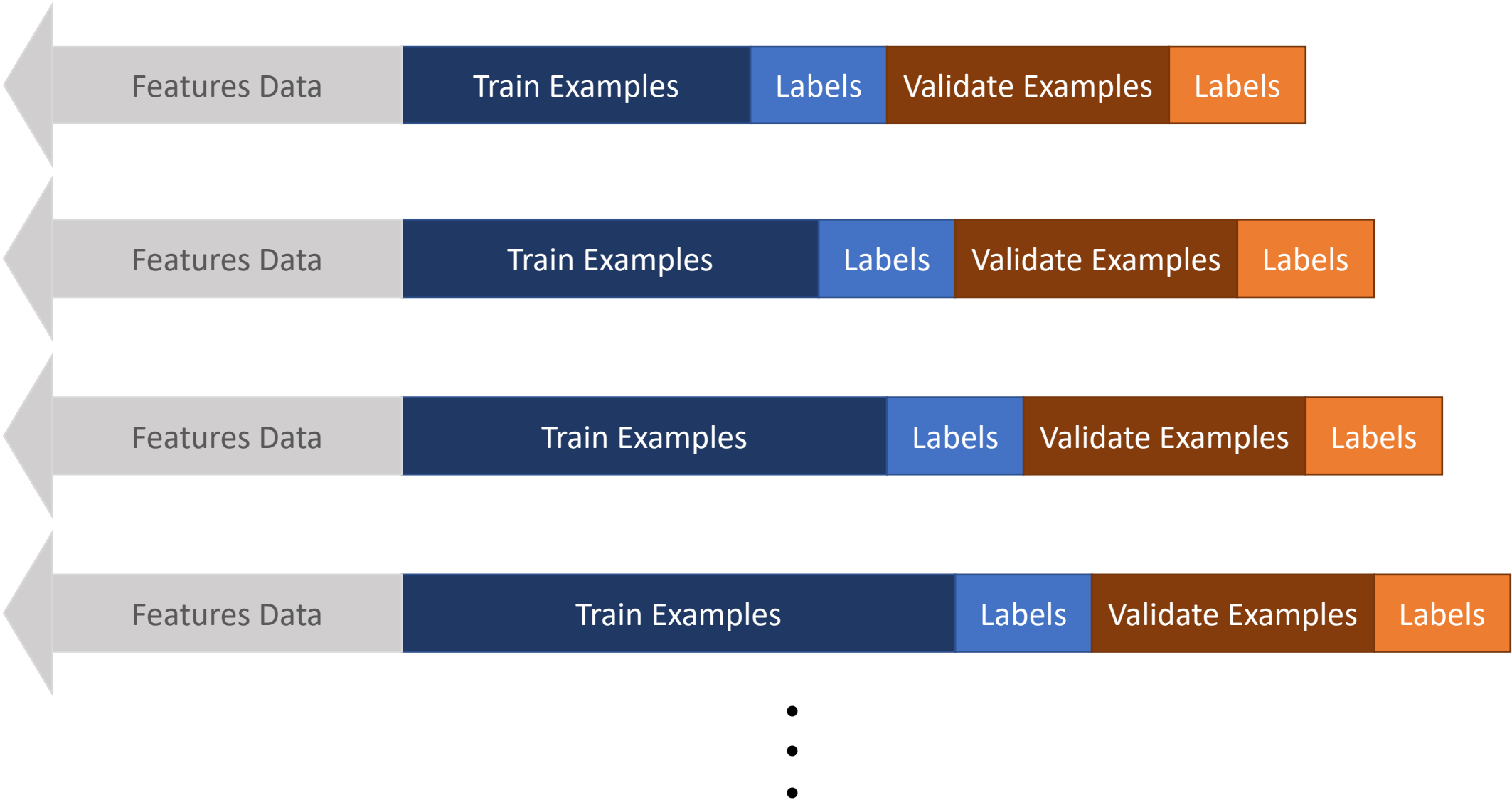
Labels

Validate Examples

Labels



Time
Splitter



INPUTS

Temporal Parameters:

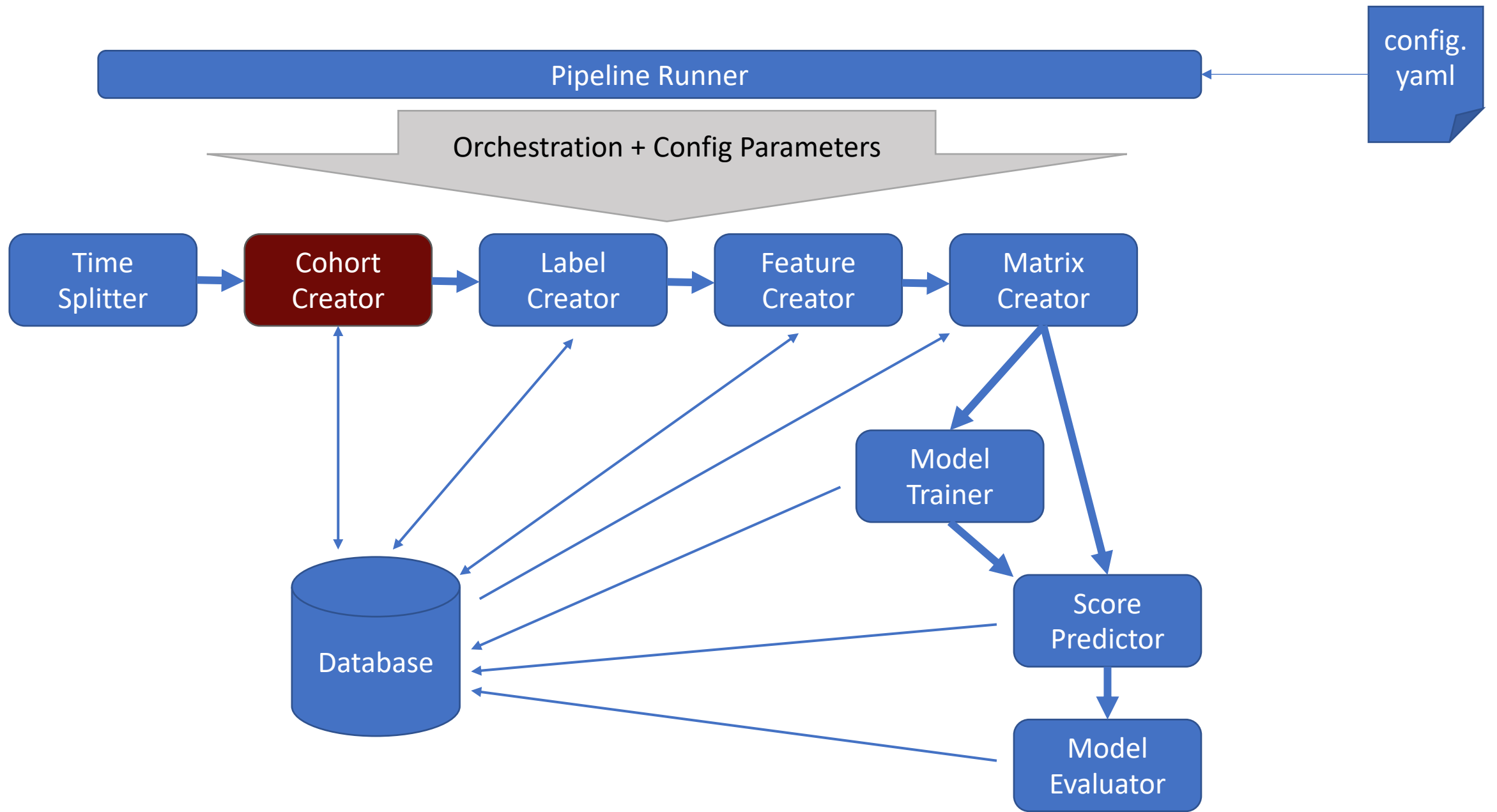
Beginning of time
End of time
Label Window
Example History
Update Frequency

OUTPUTS

Paired train/validate sets of dates:

```
[  
    (train_start_1, train_end_1),  
    (test_start_1, test_end_1)  
],  
[  
    (train_start_2, train_end_2),  
    (test_start_2, test_end_2)  
], ...
```

Note: **Not** splits of the **data**!
(you still need the full history for features)



INPUTS

Train/validate split dates

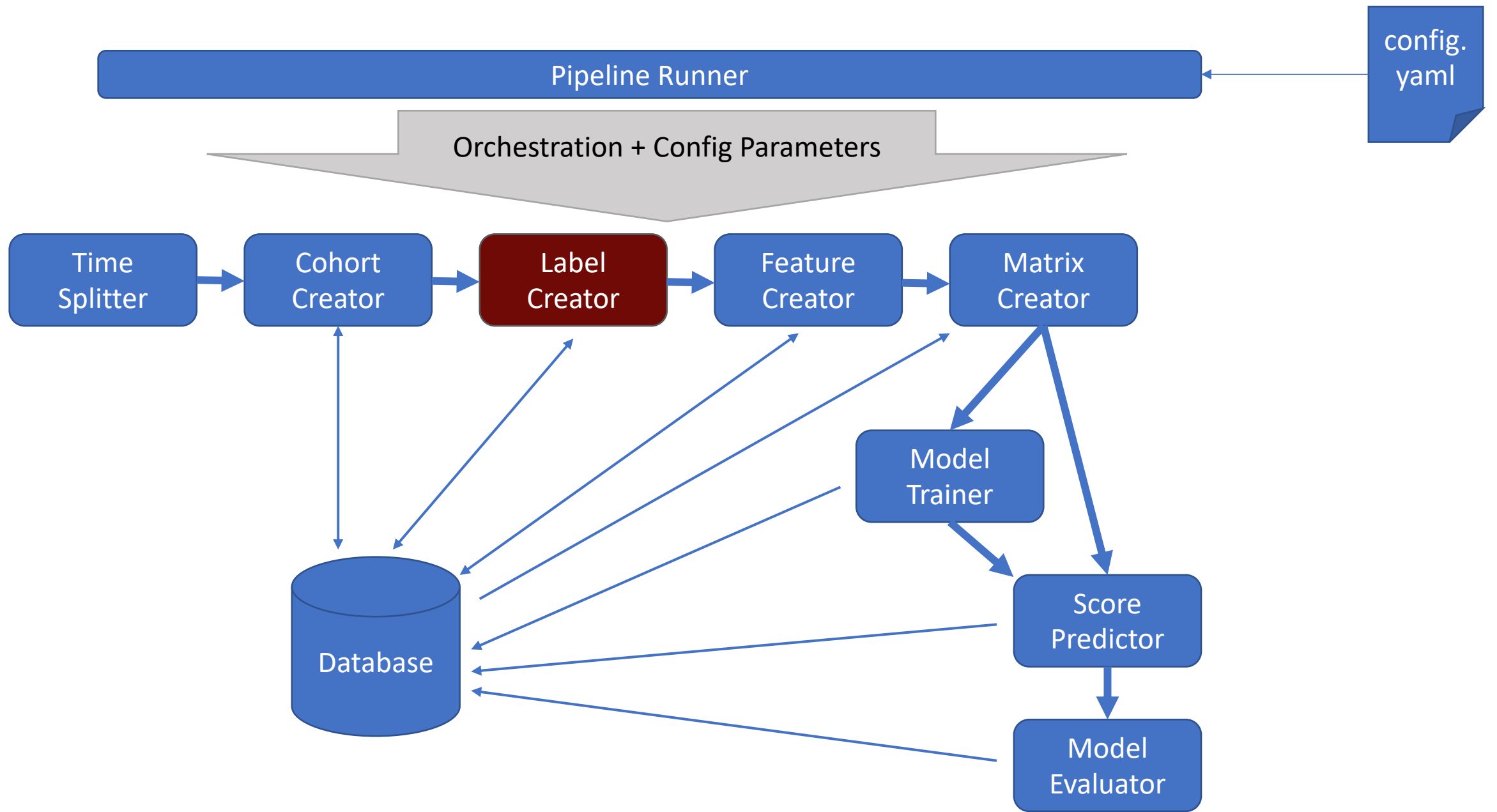
Cohort logic
(*e.g., SQL snippet in config*)

Cleaned data

OUTPUTS

Sets of entities *at a given time* that will
define rows in training/validation
matrices:

entity_id, time



Label Creator

INPUTS

Train/validate split dates

Cohort ids+dates

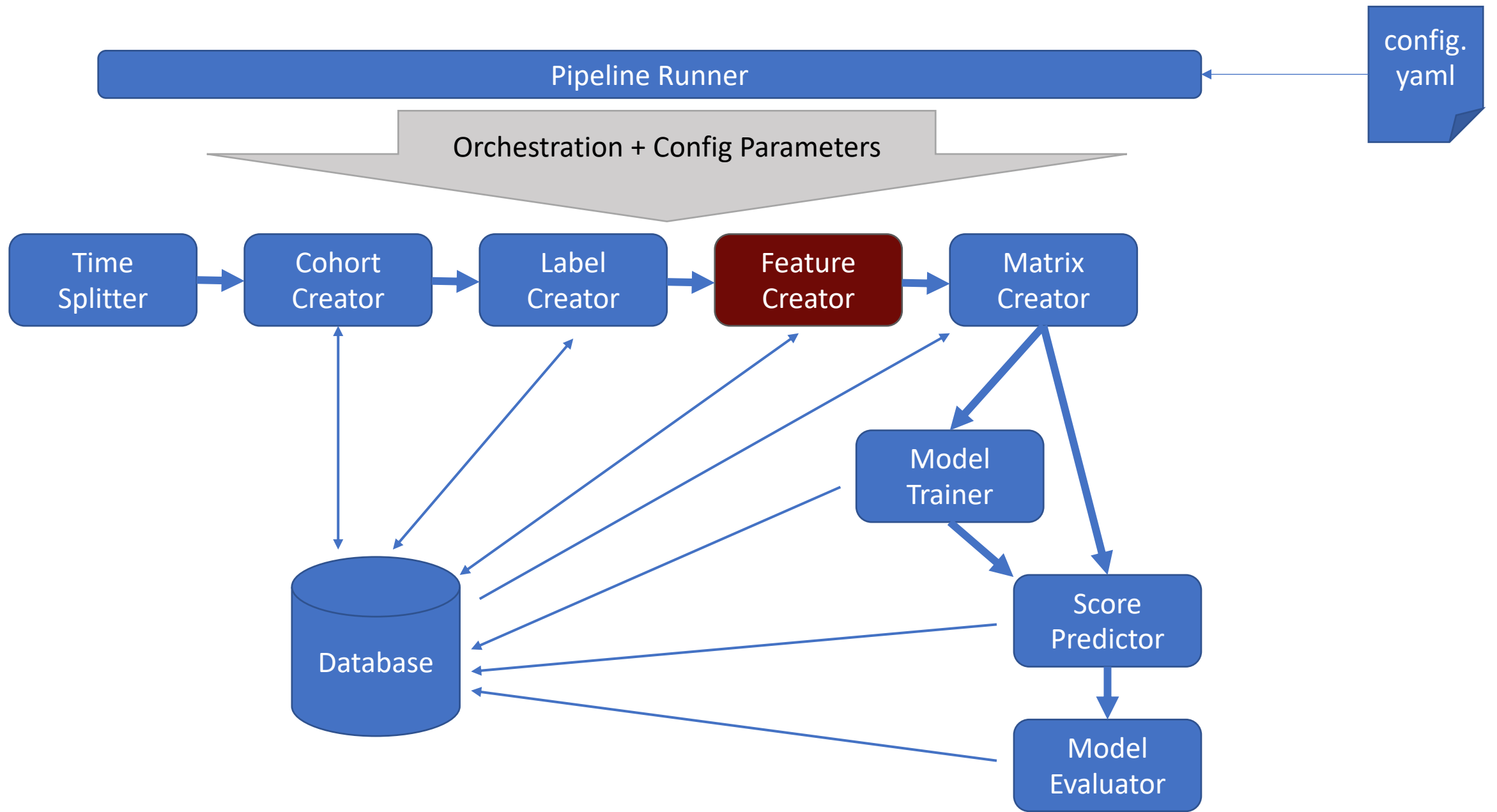
Label definition logic + window
(*e.g., via SQL snippet in config*)

Cleaned data

OUTPUTS

Label values for each entity/date pair in
the cohort:

entity_id, date, label(s)



INPUTS

Train/validate split dates

Cohort ids+dates

Feature definition logic + windows
(*e.g., via SQL snippets in config*)

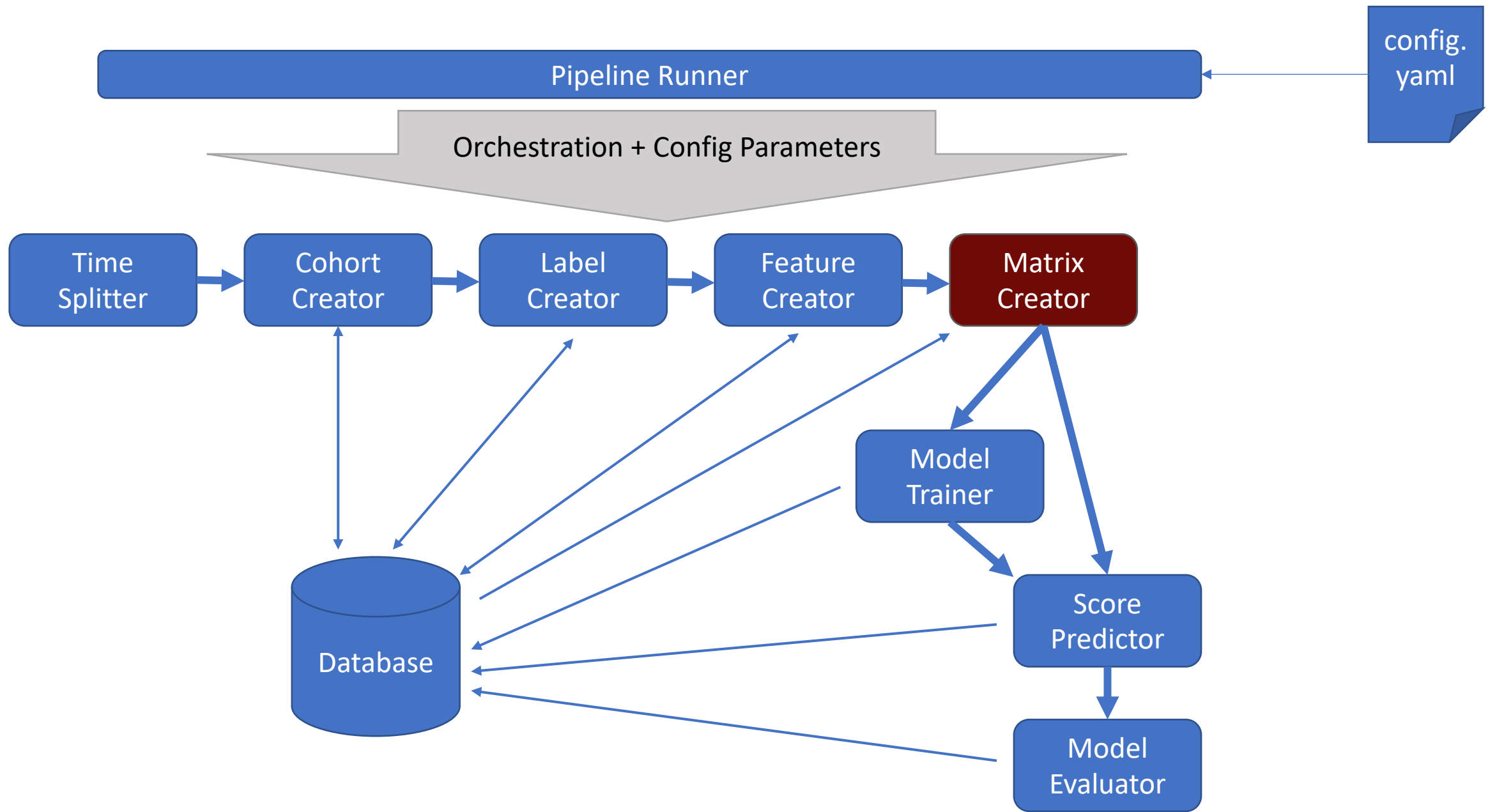
Cleaned data

OUTPUTS

Feature values for each entity/date pair
in the cohort:

entity_id, date, feature cols

Note: often useful to group related
features together for testing, etc.



INPUTS

Train/validate split dates

Cohort ids+dates

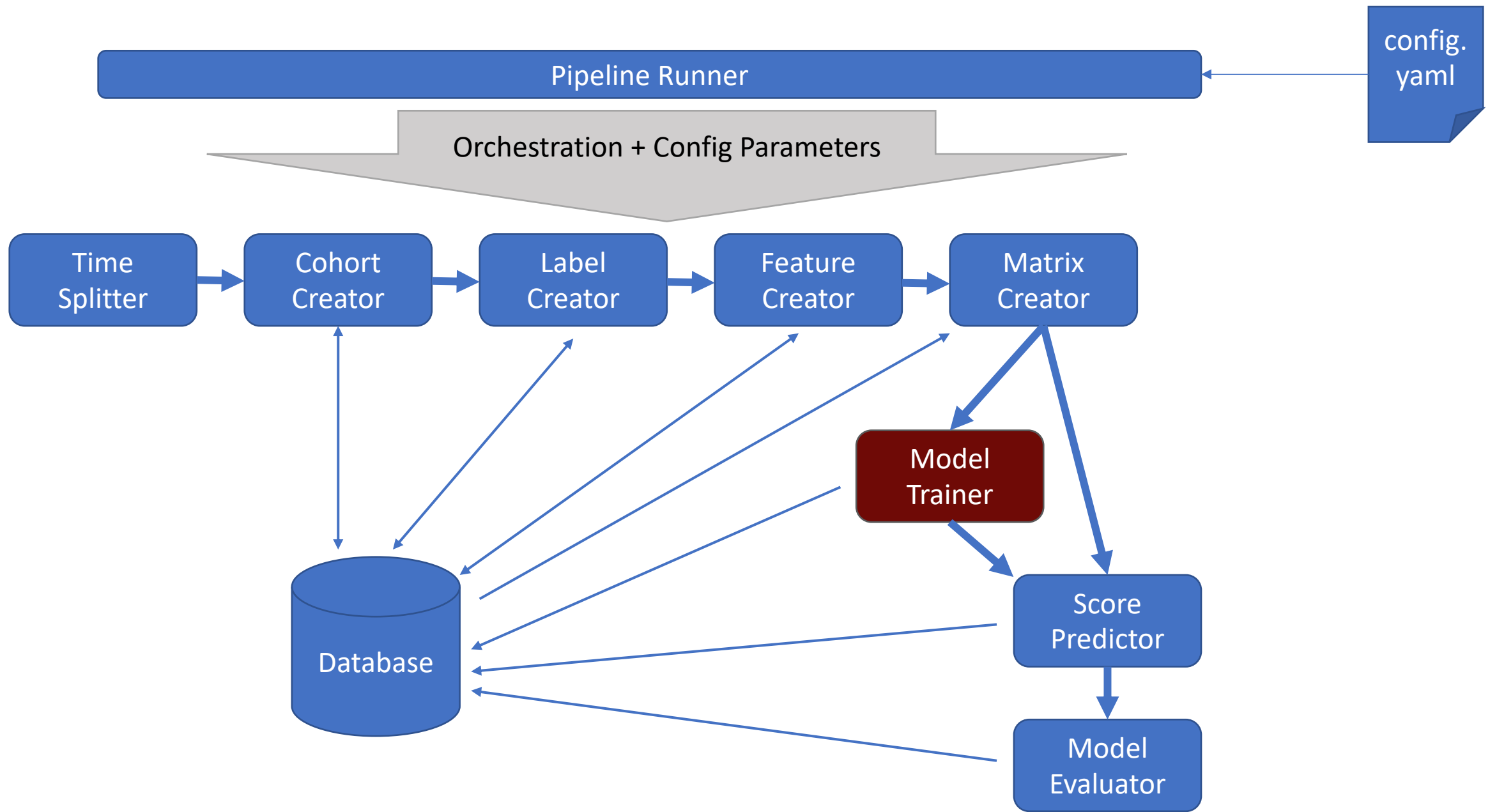
Label values

Feature values

OUTPUTS

Pairs of train + validation matrices
(np.array, pd.DataFrame, scipy.csr_matrix, etc.)

Note: all this needs to do at this point is
join the cohorts, labels, and features
together for each set of dates



INPUTS

Train Matrix
(and associated temporal metadata)

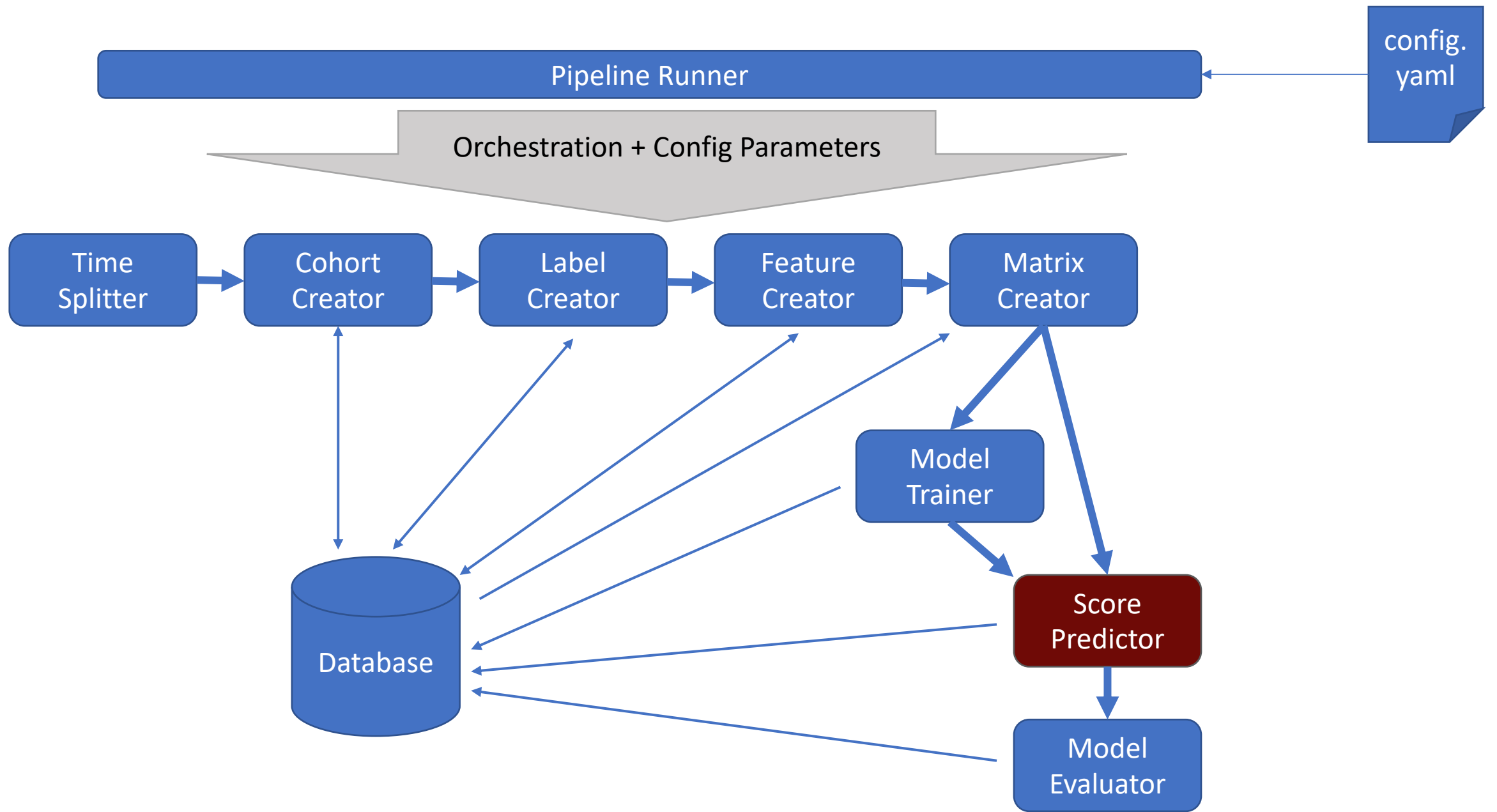
Model type + parameters
(from config)

OUTPUTS

Trained model object
(downstream + to disk)

Model metadata to database
model type, hyperparameters,
training dates, model_id

Note: Helpful to keep track of sets of models with the same parameters (type, features, hyperparameters, label definition, etc) trained on different time splits



INPUTS

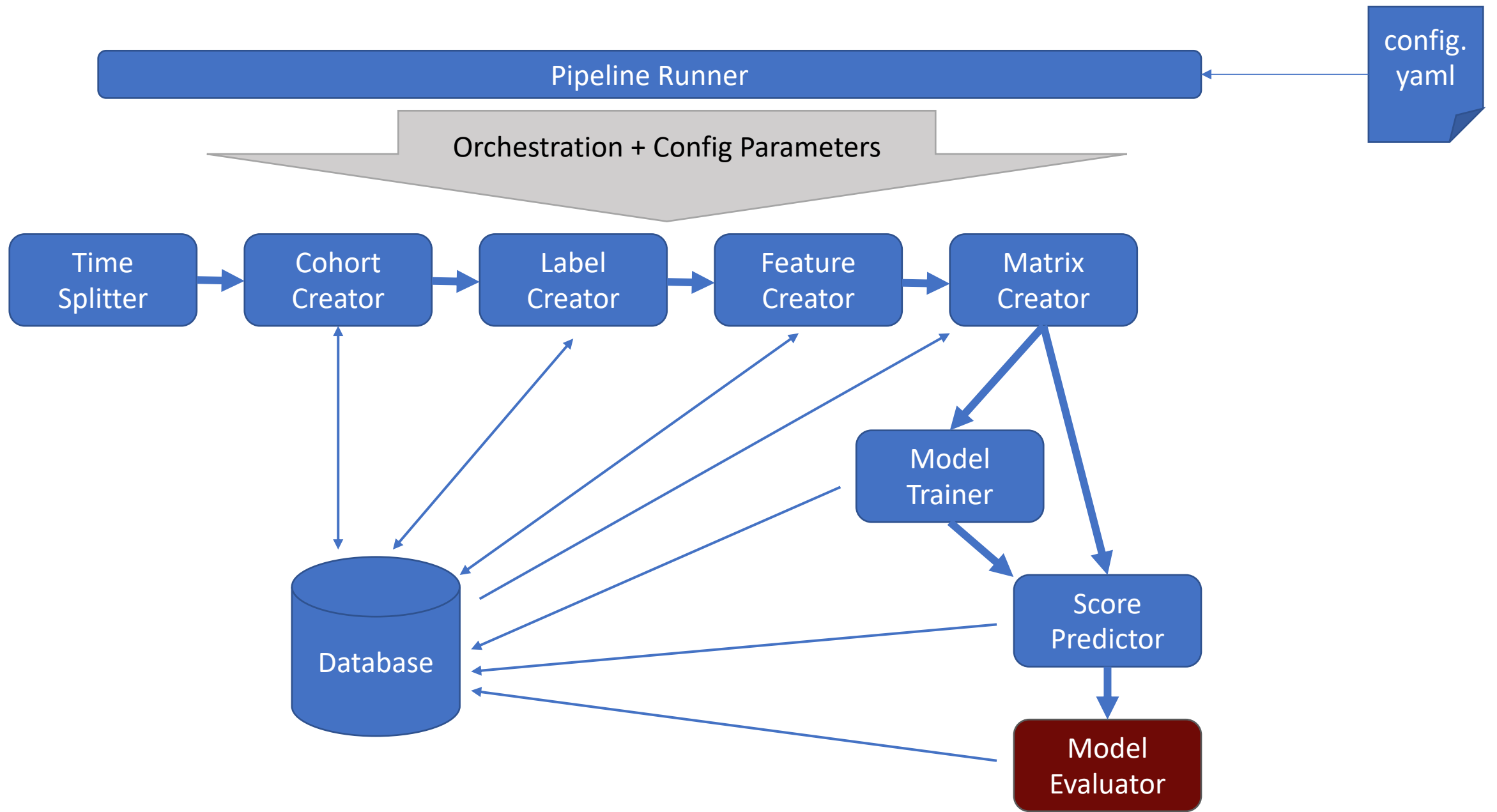
Validation Matrix
(and associated temporal metadata)

Trained model object
(and associated model_id)

OUTPUTS

Predicted scores

Note: Helpful to persist to the database for downstream analyses, but can get large, so be sure to index (and may want to make storage optional, especially during initial debugging)



INPUTS

Validation Matrix (Actual Labels)
(and associated temporal metadata)

Predicted Scores

Metric definition(s)
(from config)

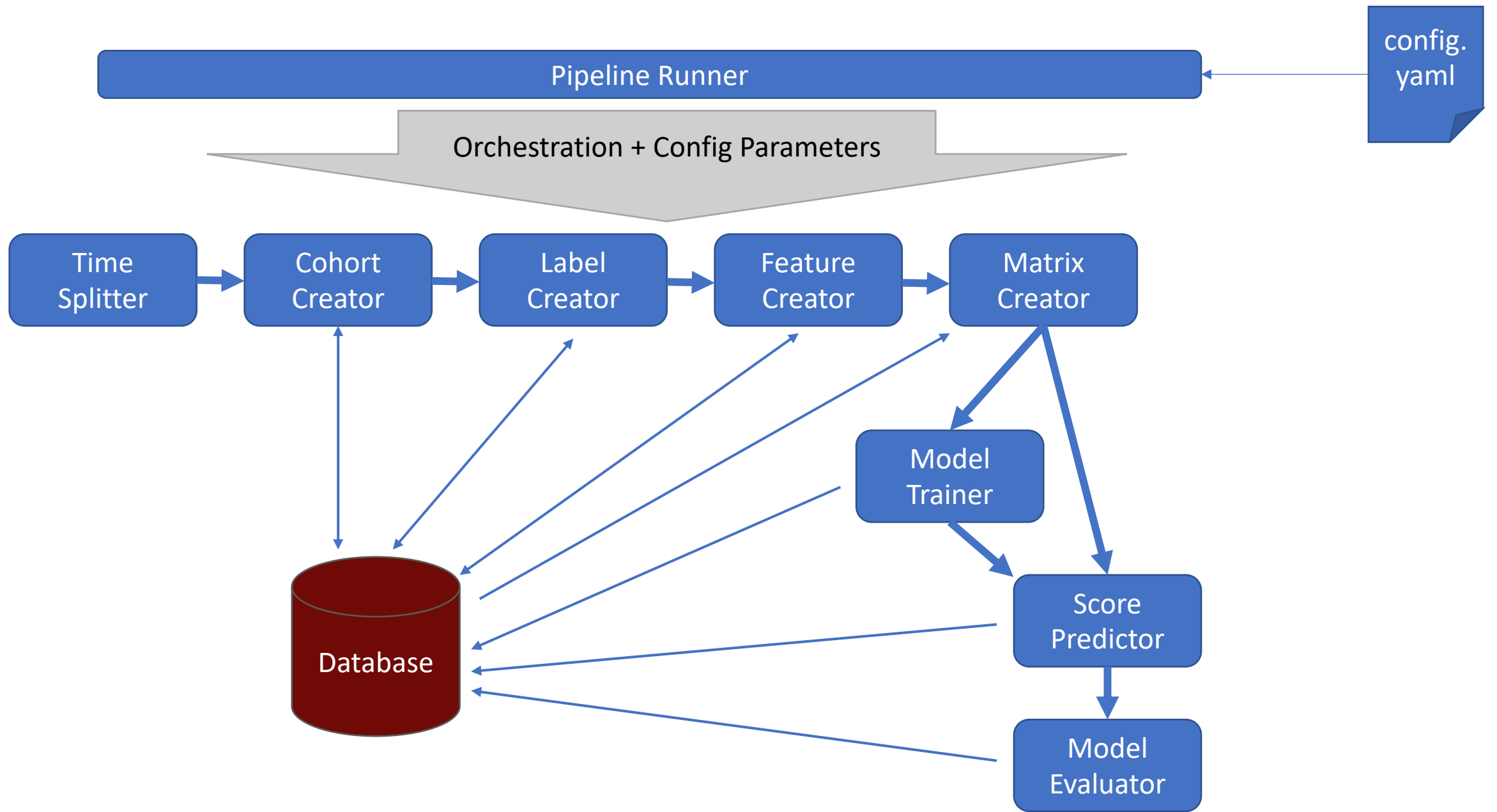
OUTPUTS

Model performance on metrics:
model_id, validation_date, metric,
parameter, value

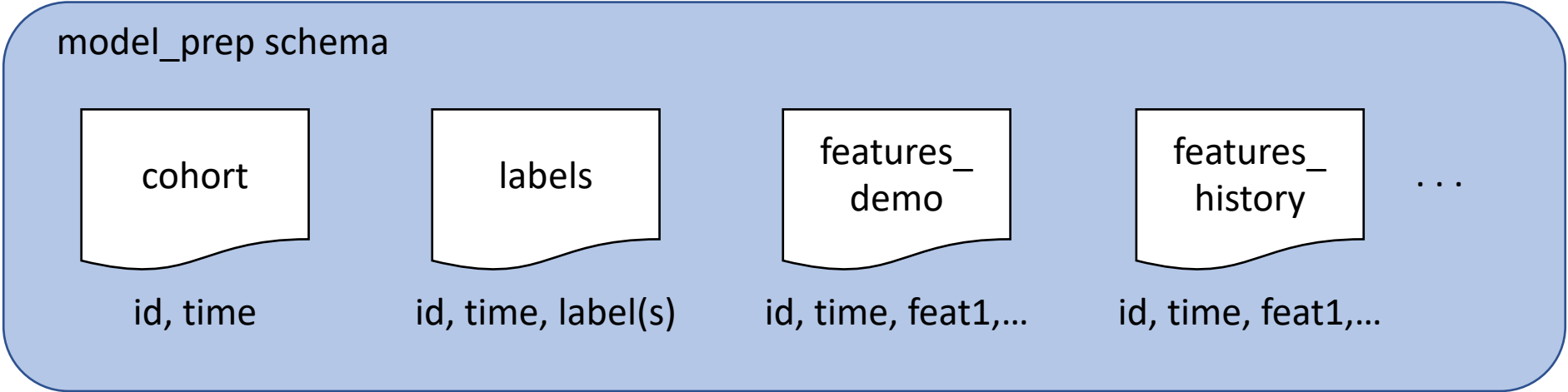
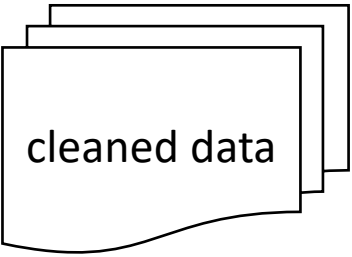
examples:

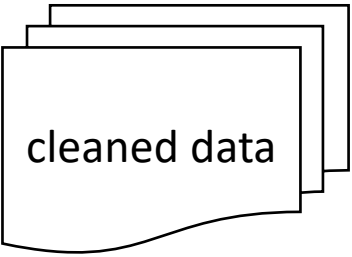
108	2015-03-14	precision	500_abs	0.62
108	2015-03-14	recall	15_pct	0.25
108	2015-03-14	recall	0.8_thresh	0.42

Note: Helpful to persist to the database
for downstream analyses









model_prep schema



id, time



id, time, label(s)



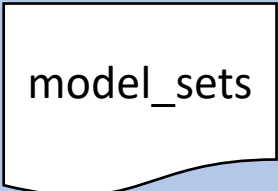
id, time, feat1,...



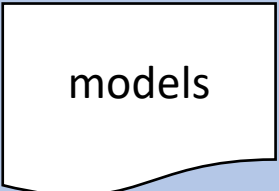
id, time, feat1,...

...

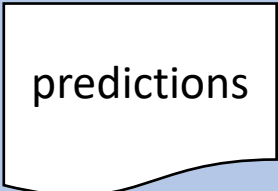
results schema



model_set_id,
type, params



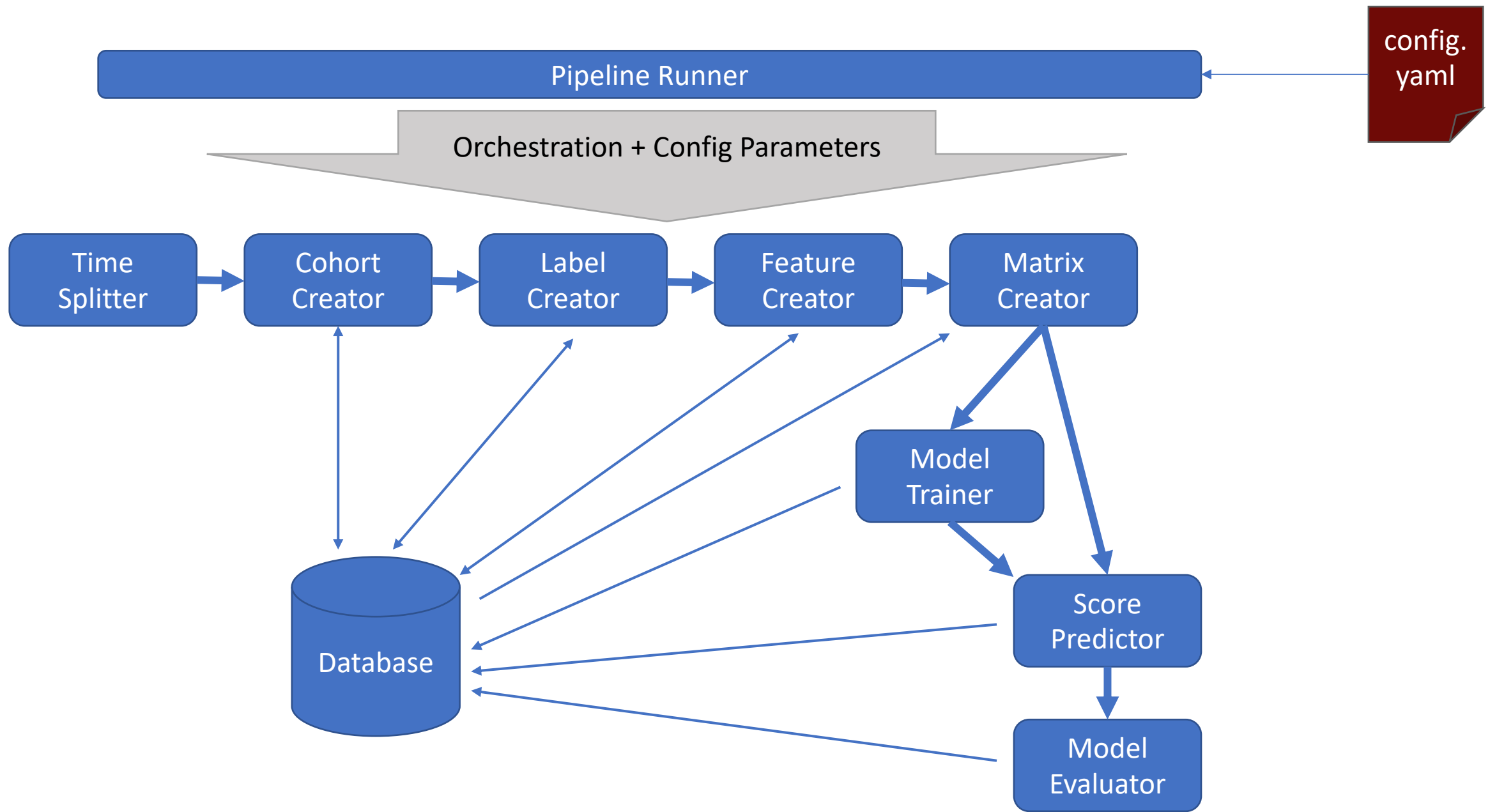
model_set_id,
model_id, time

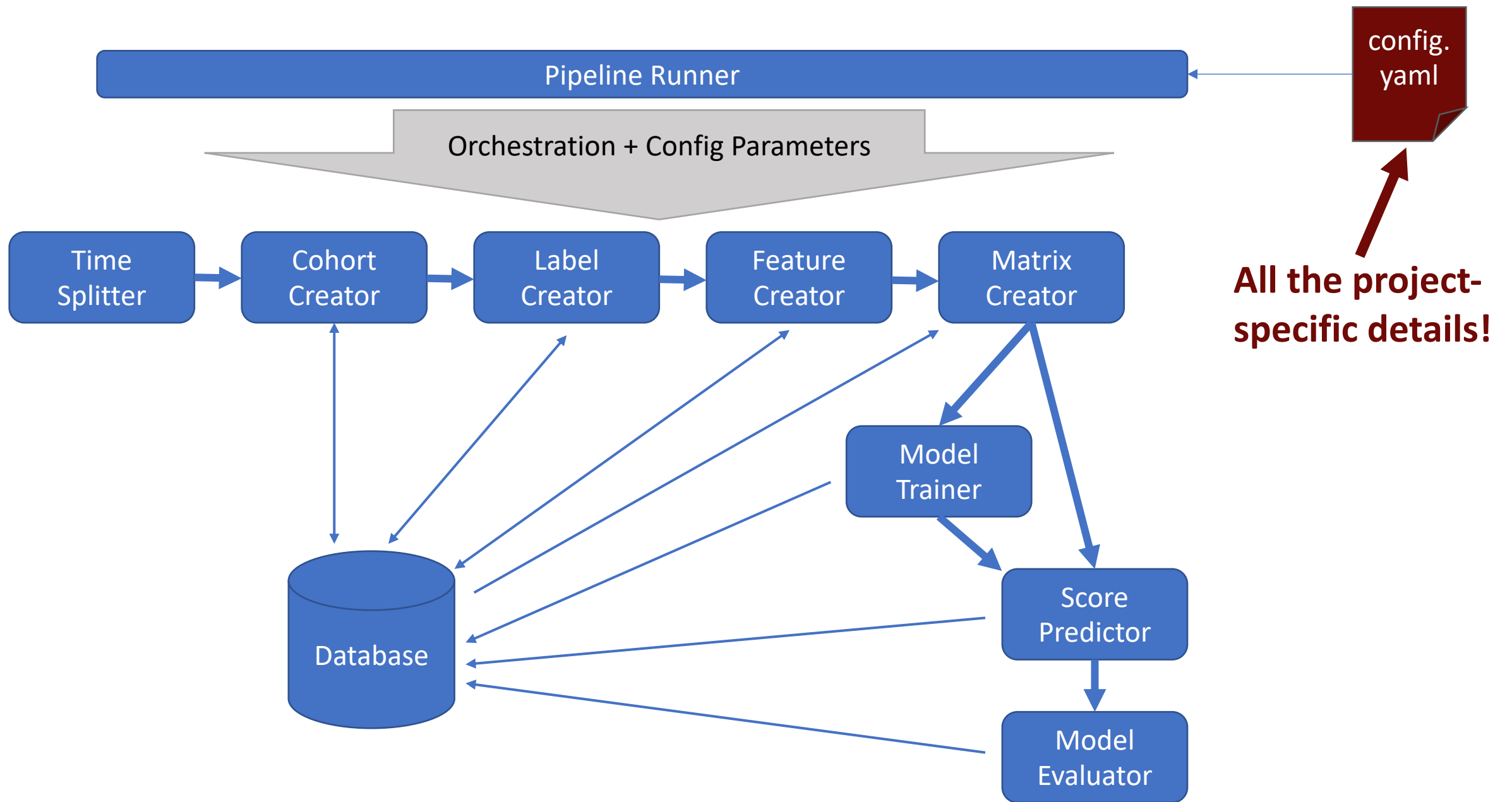


model_id, id,
time, score, label



model_id, time,
metric, value





config.
yaml

```
1 config_version: 'v6'
2
3 model_comment: 'company_inspected (test)'
4
5 temporal_config:
6   feature_start_time: '2015-01-01' # earliest date included in features
7   feature_end_time: '2018-01-01' # latest date included in features
8   label_start_time: '2015-01-01' # earliest date for which labels are available
9   label_end_time: '2018-01-01' # day AFTER last label date (all dates in any model are < this date)
10  model_update_frequency: '1y' # how frequently to retrain models
11  training_as_of_date_frequencies: '1y' # time between as of dates for same entity in train matrix
12  test_as_of_date_frequencies: '1month' # time between as of dates for same entity in test matrix
13  max_training_histories: ['10y'] # length of time included in a train matrix
14  test_durations: ['0day'] # length of time included in a test matrix (0 days will give a single prediction immediately after training end)
15  training_label_timespans: ['1month'] # time period across which outcomes are labeled in train matrices
16  test_label_timespans: ['1month'] # time period across which outcomes are labeled in test matrices
17
18 cohort_config:
19   query: |
20     select distinct on (company)
21     company as entity_id
22     from semantic.companies
23     where end_date is null or end_date <= '{as_of_date}':date
24     name: 'company'
25
26 label_config:
27   query: |
28     select
29     company as entity_id,
30     i::smallint as outcome
31     from semantic.events
32     where '{as_of_date}':date <= inspection_start_date
33     and inspection_start_date < '{as_of_date}':date + interval '{label_timespan}'
34     group by company
35   include_missing_labels_in_train_as: False
36   name: 'inspected'
37
38 feature_aggregations:
39   -
40     prefix: 'companies'
41     from_obj: |
42       (select company as entity_id, * from semantic.events) as inspections
43
44     knowledge_date_column: 'inspection_start_date'
45
46     aggregates_imputation:
47       all:
48         type: 'zero'
49       max:
50         type: 'mean'
51
52     aggregates:
53       - # number of events
54         quantity:
55           total: "n"
56
57       imputation:
58         count:
59           type: 'zero'
60
61       coltype: 'smallint'
62       metrics: ['count']
63
64   intervals:
65     - 'all'
66     - '100y'
67     - '1y'
68     - '1month'
69
```

https://github.com/dssg/direccion_trabajo_inspecciones/blob/master/experiments/test.yaml