

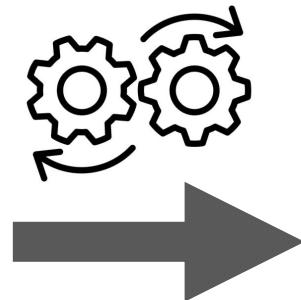
Data Leakage in Notebooks: Static Detection and Better Processes

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Why ML Models Fail in Production?

ML models



Software systems



High test accuracy

Low production accuracy

When is Test Accuracy not Reliable?

Non-representative test data



African Bush
Elephant



North America
Wild Horse

Low production accuracy



When is Test Accuracy not Reliable?

Data leakage: leak test data into model development

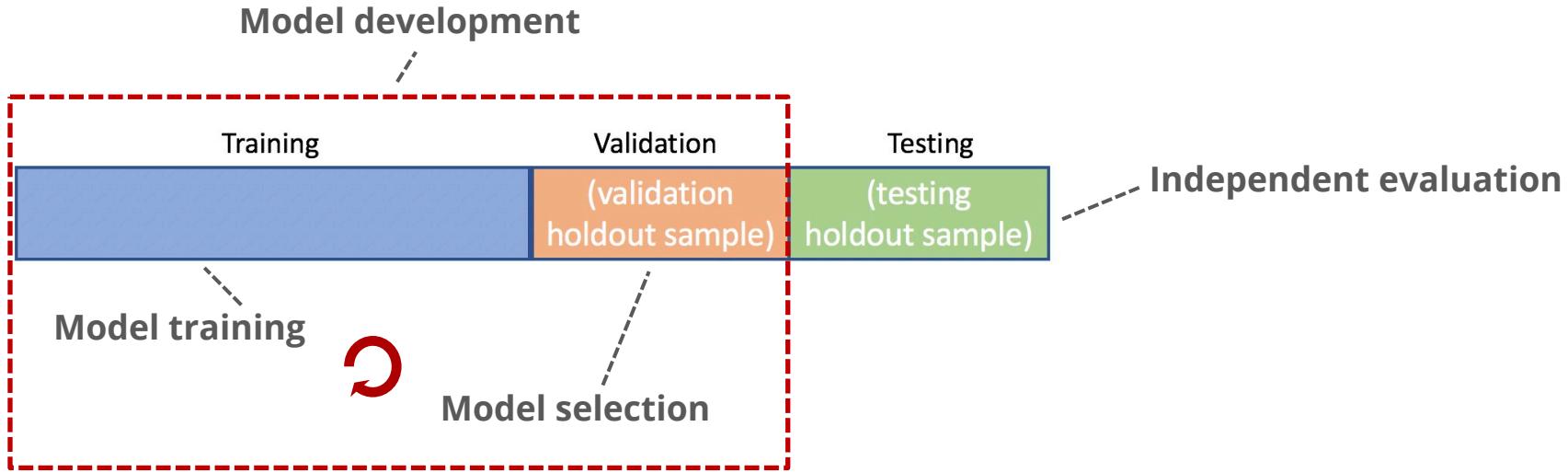
through repeated evaluation, pre-processing, and dependency

We use **static analysis** to detect data leakage in **~281k notebooks**

~81k GitHub repositories created in Sep. 2021

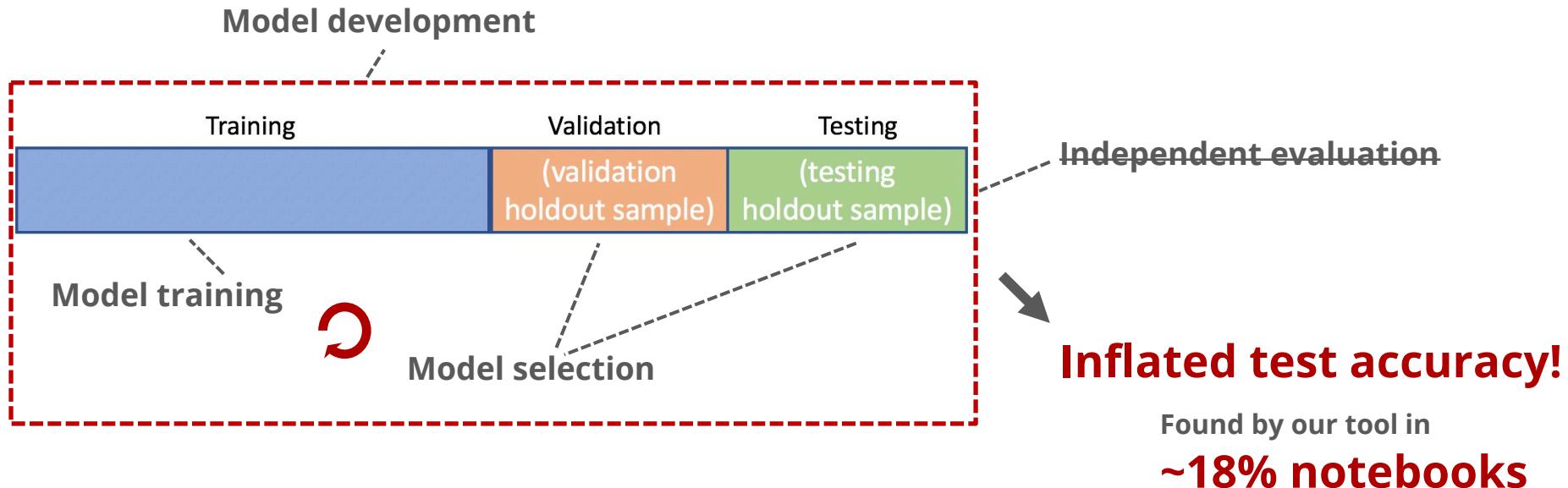
2 top Kaggle competitions

Principle of Independent Evaluation



Data Leakage #1: through Repeated Evaluation

Models overfit to test data after repeated evaluation



Data Leakage #2: through Preprocessing

Peeking at test data in competitions is common

Training data

	the	red	dog	cat	eats	food
1. the red dog	→ 1	1	1	0	0	0
2. cat eats dog	→ 0	0	1	1	1	0
3. dog eats food	→ 0	0	1	0	1	1
4. red cat eats	→ 0	1	0	1	1	0

Test data

Unknown words

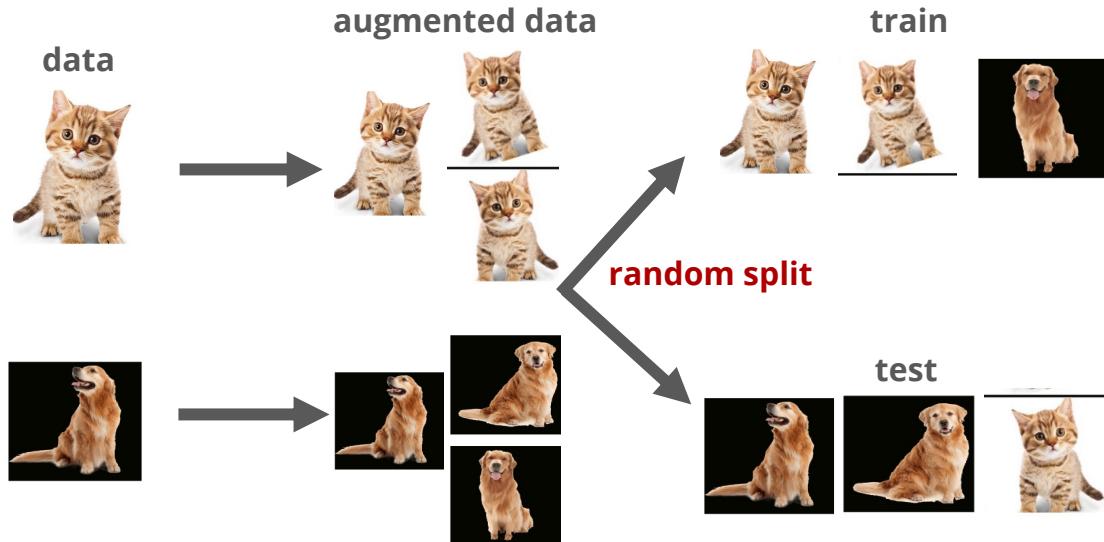
Different distribution

Inflated test accuracy!

Found by our tool in
~12% notebooks

Data Leakage #3: through Dependency

Data augmentation could introduce dependency



Train/test dependency

Inflated test accuracy!

Found by our tool in
~6% notebooks

Data Leakage is Prevalent in Practice

~281k notebooks from GitHub and Kaggle

~30% GitHub notebooks have data leakage issues

33% assignments (keyword: 'assignment', 'homework')

20% popular notebooks (≥ 10 stars)

16% tutorials (keyword: 'this tutorial')

55% competition solutions leak through preprocessing

Leakage Exhibits Non-local Patterns

Leakage and training are often far apart

span >20% of the whole notebook in >50% cases

Hard for manual detection!

Leakage →

```
Leakage happens here
X, y = SMOTE().fit_resample(X_raw, y_raw)

Lots of code in between

import pandas as pd
from sklearn.feature_selection import SelectPercentile, chi2
from sklearn.model_selection import LinearRegression, Ridge
X_0, y = load_data()
select = SelectPercentile(chi2, percentile=50)
select.fit(X_0)
X_0 = select.transform(X_0)

X_train, y_train, X_test, y_test = train_test_split(X, y)
lr = LinearRegression()
lr.fit(X_train, y_train)
lr.score = lr.score(X_test, y_test)

ridge = Ridge()
ridge.fit(X, y)
ridge.score = ridge.score(X_test, y_test)

final_model = lr if lr.score > ridge.score else ridge
```

```
results = []
for clf, name in (
    (DecisionTreeClassifier(), "Decision Tree"),
    (Perceptron(), "Perceptron")):
    clf.fit(X_train, y_train)
    pred = clf.predict(X_test)
    score = metrics.accuracy_score(y_test, pred)
    results.append(score, name)

wordsVectorizer = CountVectorizer().fit(text)
wordsVector = wordsVectorizer.transform(text)

invTransformer = TfidfTransformer().fit(wordsVector)
invFreqOfWords = invTransformer.transform(wordsVector)

X = pd.DataFrame(invFreqOfWords.toarray())
train, test, spanLabelTrain, spanLabelTest = train_test_split(X, y, test_size = 0.5)
predictAndReport(train, test)
```

```
X_selected = SelectKBest(k=25).fit_transform(X, y)
X_train, X_test, y_train, y_test = train_test_split(
    X_selected, y, random_state=42)
gbc = GradientBoostingClassifier(random_state=1)
gbc.fit(X_train, y_train)

y_pred = gbc.predict(X_test)
accuracy_score(y_test, y_pred)

from sklearn.pipeline import make_pipeline
X_train, X_test, y_train, y_test = train_test_split(
    X, y, random_state=42)
pipeline = make_pipeline(SelectKBest(k=25),
    GradientBoostingClassifier(random_state=1))
pipeline.fit(X_train, y_train)

y_pred = pipeline.predict(X_test)
accuracy_score(y_test, y_pred)
```

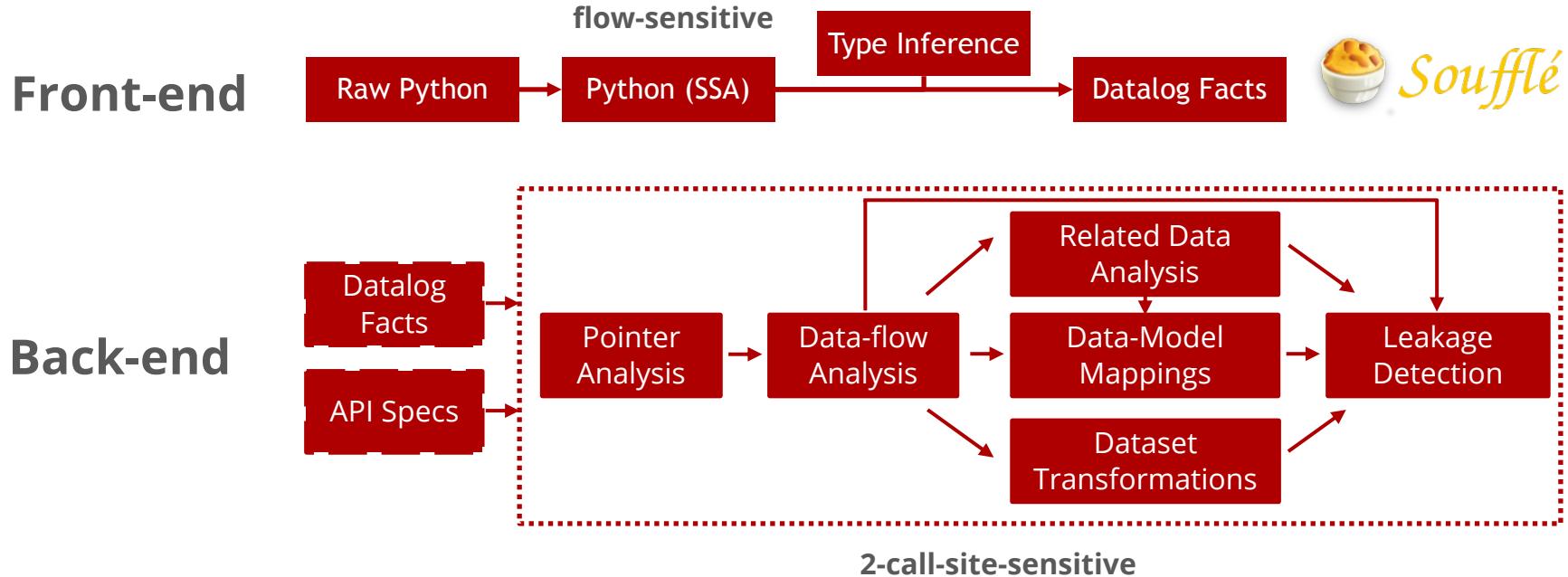
Training →

```
Training

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
rf = RandomForestClassifier().fit(X_train, y_train)
```

Could we statically detect data leakage?

Statically Detecting Data Leakage



Walkthrough Example

```
import pandas as pd
from sklearn.feature_selection import SelectPercentile, chi2
from sklearn.model_selection import LinearRegression, train_test_split
data = pd.read_csv('data.csv')
X_raw = data.drop('label', axis=1)
y = data['label']

select = SelectPercentile(chi2, percentile=50)
select.fit(X_raw)
X = select.transform(X_raw)

X_train, y_train, X_test, y_test = train_test_split(X, y)
lr = LinearRegression()
lr.fit(X_train, y_train)
lr_score = lr.score(X_test, y_test)
```

} Load data

} Feature selection

} Model training & evaluation

Test Data is Used for Feature Selection

```
import pandas as pd
from sklearn.feature_selection import SelectPercentile, chi2
from sklearn.model_selection import LinearRegression, train_test_split
data = pd.read_csv('data.csv')
X_raw = data.drop('label', axis=1)
y = data['label']

select = SelectPercentile(chi2, percentile=50)
select.fit(X_raw)
X = select.transform(X_raw)      } Feature selection
                                } Preprocessing Leakage

X_train, y_train, X_test, y_test = train_test_split(X, y)
lr = LinearRegression()
lr.fit(X_train, y_train)
lr_score = lr.score(X_test, y_test)
```

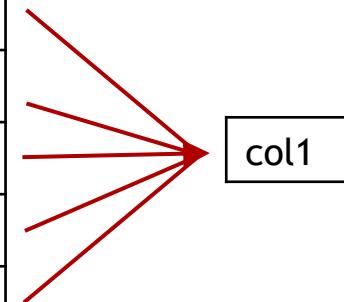
When is an Operation Leakage-inducing?

```
import pandas as pd
from sklearn.feature_selection import SelectPercentile, chi2
from sklearn.model_selection import LinearRegression, train_test_split
data = pd.read_csv('data.csv')
X_raw = data.drop('label', axis=1)
y = data['label']

select = SelectPercentile(chi2, percentile=50)
select.fit(X_raw)
X = select.transform(X_raw)

X_train, y_train, X_test, y_test = train_test_split(X, y)
lr = LinearRegression()
lr.fit(X_train, y_train)
lr_score = lr.score(X_test, y_test)
```

	col1	col2
1	3	4
2	0	1
3	6	3
4	-3	6
5	2	1



col1

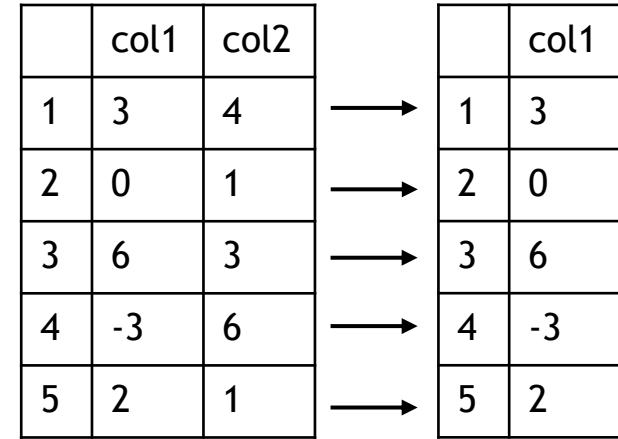
Computing across rows could lead to leakage

When is an Operation Leakage-inducing?

```
import pandas as pd
from sklearn.feature_selection import SelectPercentile, chi2
from sklearn.model_selection import LinearRegression, train_test_split
data = pd.read_csv('data.csv')
X_raw = data.drop('label', axis=1)
y = data['label']

select = SelectPercentile(chi2, percentile=50)
select.fit(X_raw)
X = select.transform(X_raw)

X_train, y_train, X_test, y_test = train_test_split(X, y)
lr = LinearRegression()
lr.fit(X_train, y_train)
lr_score = lr.score(X_test, y_test)
```



The diagram illustrates a transformation of a 5x3 matrix into a 5x2 matrix. On the left, a 5x3 matrix is shown with columns labeled 'col1' and 'col2'. The rows are indexed 1 to 5. The data is as follows:

	col1	col2
1	3	4
2	0	1
3	6	3
4	-3	6
5	2	1

On the right, a 5x2 matrix is shown with column 'col1'. The rows are indexed 1 to 5. The data is as follows:

	col1
1	3
2	0
3	6
4	-3
5	2

Arrows point from each row of the 5x3 matrix to its corresponding row in the 5x2 matrix, indicating that the second column has been dropped.

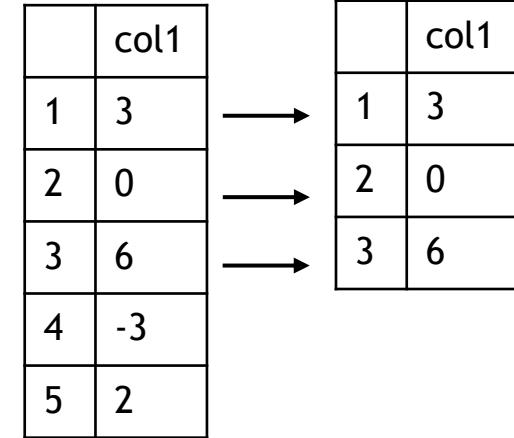
Computing each row independently is safe

When is an Operation Leakage-inducing?

```
import pandas as pd
from sklearn.feature_selection import SelectPercentile, chi2
from sklearn.model_selection import LinearRegression, train_test_split
data = pd.read_csv('data.csv')
X_raw = data.drop('label', axis=1)
y = data['label']

select = SelectPercentile(chi2, percentile=50)
select.fit(X_raw)
X = select.transform(X_raw)

X_train, y_train, X_test, y_test = train_test_split(X, y)
lr = LinearRegression()
lr.fit(X_train, y_train)
lr_score = lr.score(X_test, y_test)
```



	col1
1	3
2	0
3	6
4	-3
5	2

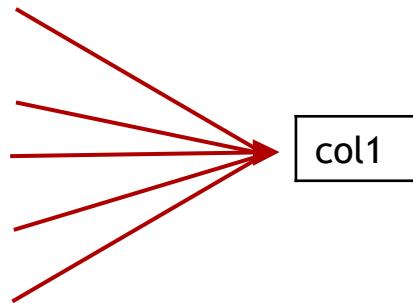
	col1
1	3
2	0
3	6
4	-3
5	2

Computing each row independently is safe

Reduce-like Operations could Lead to Leakage

reduce

	col1	col2
1	3	4
2	0	1
3	6	3
4	-3	6
5	2	1



map

	col1	col2
1	3	4
2	0	1
3	6	3
4	-3	6
5	2	1

filter

	col1
1	3
2	0
3	6
4	-3
5	2

Detecting Data Leakage with Data-flow

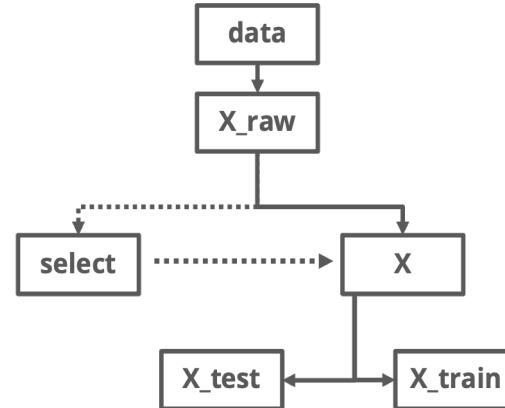
```
import pandas as pd
from sklearn.feature_selection import SelectPercentile, chi2
from sklearn.model_selection import LinearRegression, train_test_split
data = pd.read_csv('data.csv')
X_raw = data.drop('label', axis=1)
y = data['label']

select = SelectPercentile(chi2, percentile=50)
select.fit(X_raw)
X = select.transform(X_raw)      Preprocessing Leakage!

X_train, y_train, X_test, y_test = train_test_split(X, y)
lr = LinearRegression()
lr.fit(X_train, y_train)
lr_score = lr.score(X_test, y_test)
```

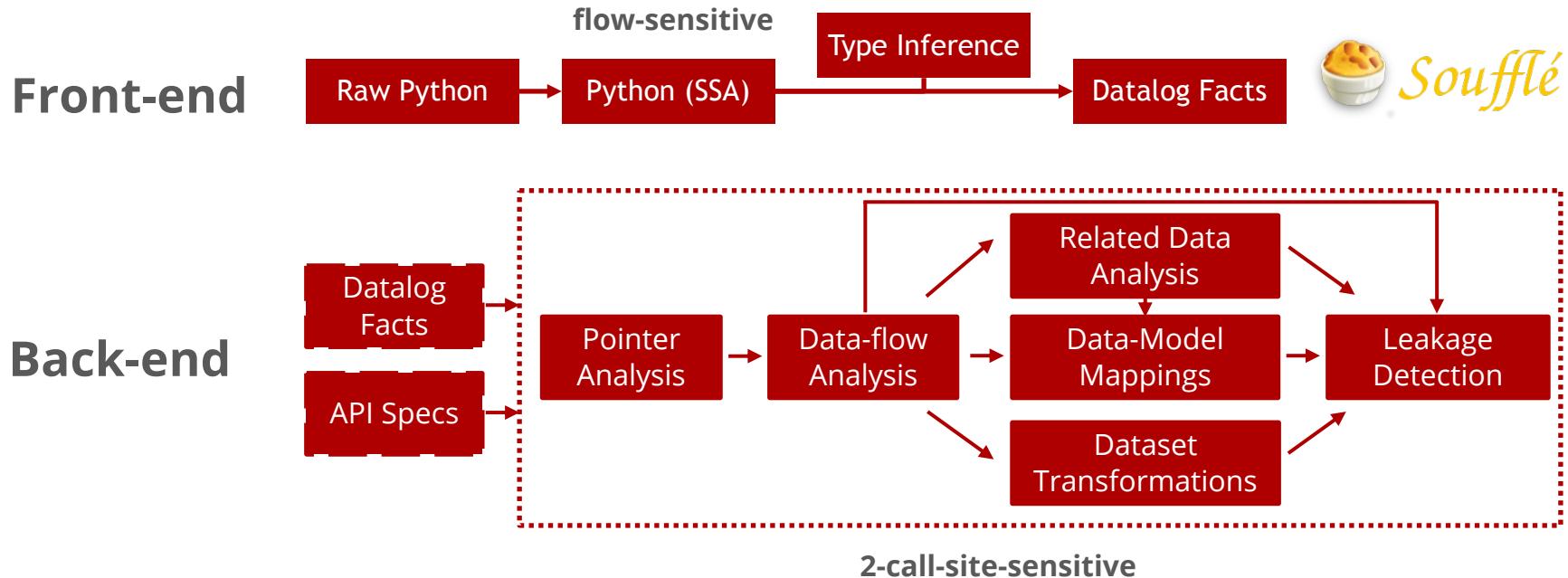
reduce

map/filter



*There are more subtleties in tracking data-flow and determining whether two datasets are related: see our paper for details.

Implementation



Evaluation: Accuracy & Efficiency

93% accuracy from comparing results with 100 manually labeled sample notebooks

3 seconds (avg.) of analysis on a standard desktop with Intel Xeon CPU and 32GB memory

Recall: Data Leakage is Prevalent in Practice

~30% GitHub notebooks have data leakage issues

33% assignments

20% popular notebooks

16% tutorials

55% competition solutions leaks through preprocessing

Could we avoid data leakage in practice?

Data Leakage: Better Processes

Static analysis as **warnings** in notebooks

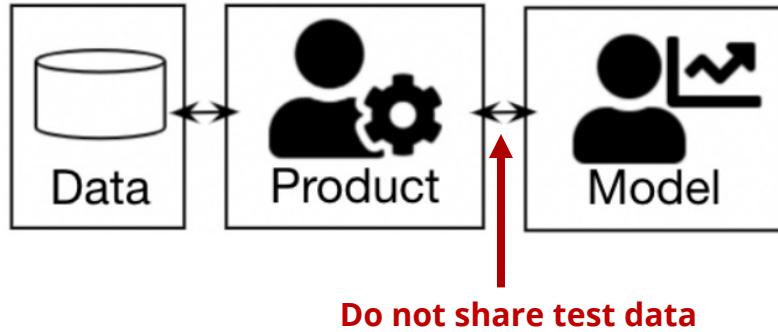
```
import pandas as pd
from sklearn.feature_selection import SelectPercentile, chi2
from sklearn.model_selection import LinearRegression, train_test_split
data = pd.read_csv('data.csv')
X_raw = data.drop('label', axis=1)
y = data['label']

select = SelectPercentile(chi2, percentile=50)
select.fit(X_raw) data leakage (preprocessing)
X = select.transform(X_raw)

X_train, y_train, X_test, y_test = train_test_split(X, y)
lr = LinearRegression()
lr.fit(X_train, y_train) train
lr_score = lr.score(X_test, y_test) test
```

Data Leakage: Better Processes

Limited access to test label/data



Data Leakage: Better Processes

API Design to prevent leakage

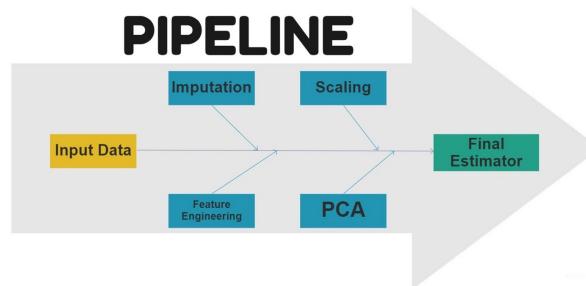
```
X_selected = SelectKBest(k=25).fit_transform(X, y)

X_train, X_test, y_train, y_test = train_test_split(
    X_selected, y, random_state=42)
gbc = GradientBoostingClassifier(random_state=1)
gbc.fit(X_train, y_train)

y_pred = gbc.predict(X_test)
accuracy_score(y_test, y_pred)
```

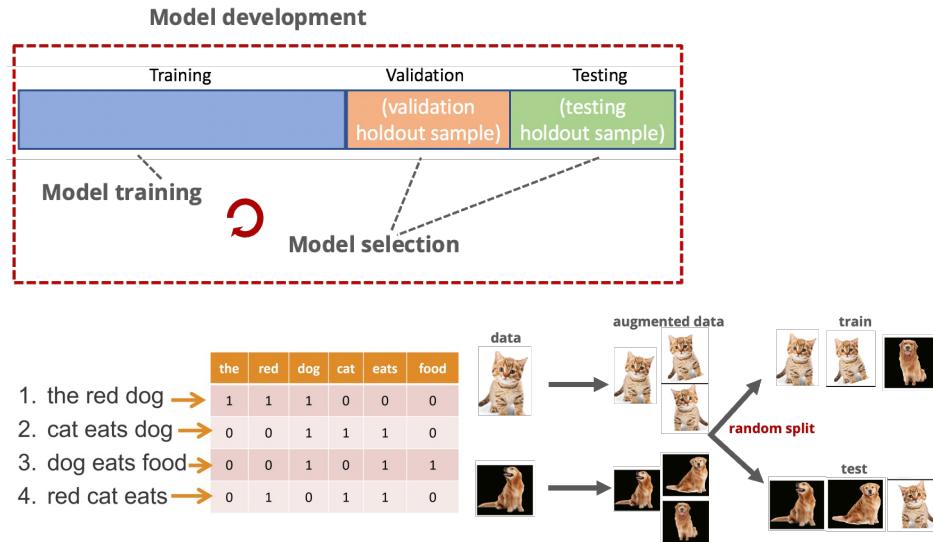
```
from sklearn.pipeline import make_pipeline
X_train, X_test, y_train, y_test = train_test_split(
    X, y, random_state=42)
pipeline = make_pipeline(SelectKBest(k=25),
                        GradientBoostingClassifier(random_state=1))
pipeline.fit(X_train, y_train)

y_pred = pipeline.predict(X_test)
accuracy_score(y_test, y_pred)
```



Takeaways

Data Leakage is **prevalent** in practice
(in ~30% GitHub notebooks)



Static analysis and better process designs could help

```
import pandas as pd
from sklearn.feature_selection import SelectPercentile, chi2
from sklearn.model_selection import LinearRegression, train_test_split
data = pd.read_csv('data.csv')
X_raw = data.drop('label', axis=1)
y = data['label']

select = SelectPercentile(chi2, percentile=50)
select.fit(X_raw) data leakage (preprocessing)
X = select.transform(X_raw)

X_train, y_train, X_test, y_test = train_test_split(X, y)
lr = LinearRegression()
lr.fit(X_train, y_train) train
lr.score = lr.score(X_test, y_test) test
```



Bonus: Practical Impact of Data Leakage

Often marginal accuracy differences

Data leakage makes models
“learn” from random data

Data leakage leads to flawed
experiments and wasted time

```
1 import numpy as np
2 # generate random data
3 n_samples, n_features, n_classes = 200, 10000, 2
4 rng = np.random.RandomState(42)
5 X = rng.standard_normal((n_samples, n_features))
6 y = rng.choice(n_classes, n_samples)
7
8 # leak test data through feature selection
9 X_selected = SelectKBest(k=25).fit_transform(X, y)
10
11 X_train, X_test, y_train, y_test = train_test_split(
12     X_selected, y, random_state=42)
13 gbc = GradientBoostingClassifier(random_state=1)
14 gbc.fit(X_train, y_train)
15
16 y_pred = gbc.predict(X_test)
17 accuracy_score(y_test, y_pred)
18 # expected accuracy ~0.5; reported accuracy 0.76
```
