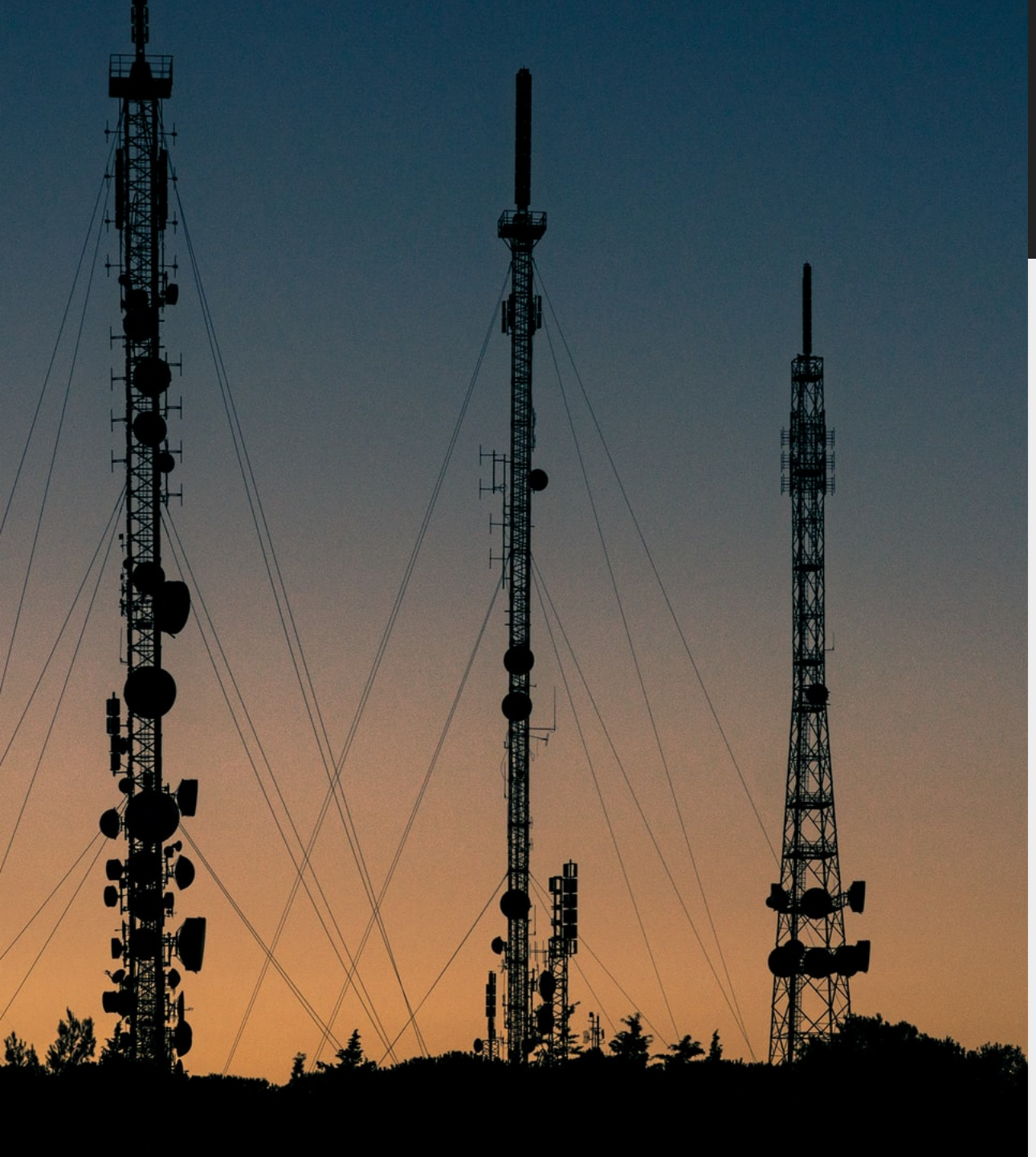
How to Guarantee *No One* Understands What You Did in Your Machine Learning Project

Jesper Dramsch

Motivation

💻 + 🧠 = Awesome!



Outline

- Communication
- Ethics
- Explainability
- Data Visualizations
- Interactivity
- Model Validation

How do People Understand?

- They understand your language
- Relate things to what they already know
- Feel heard
- Have concerns addressed

Communicate like a Pro

- Ignore subject matter expertise
- Dismiss existing solutions
- No need to build trust
- Never set expectations
- Especially not about labelling

Ethical Considerations

- Privacy concerns
- Anonymisation
- Problematic Applications
- Discrimination
- Policing

Be Super Specific about Models

Stakeholders love nothing more than a detailed read-out of

- Parameters
- Model size
- Learning Rate Schedules
- Hours of Training

Avoid These Tools to be Extra Confusing

Baseline Models

Existing or interpretable models to compare to

Baseline Models

by Jesper Dramsch

Baseline Models

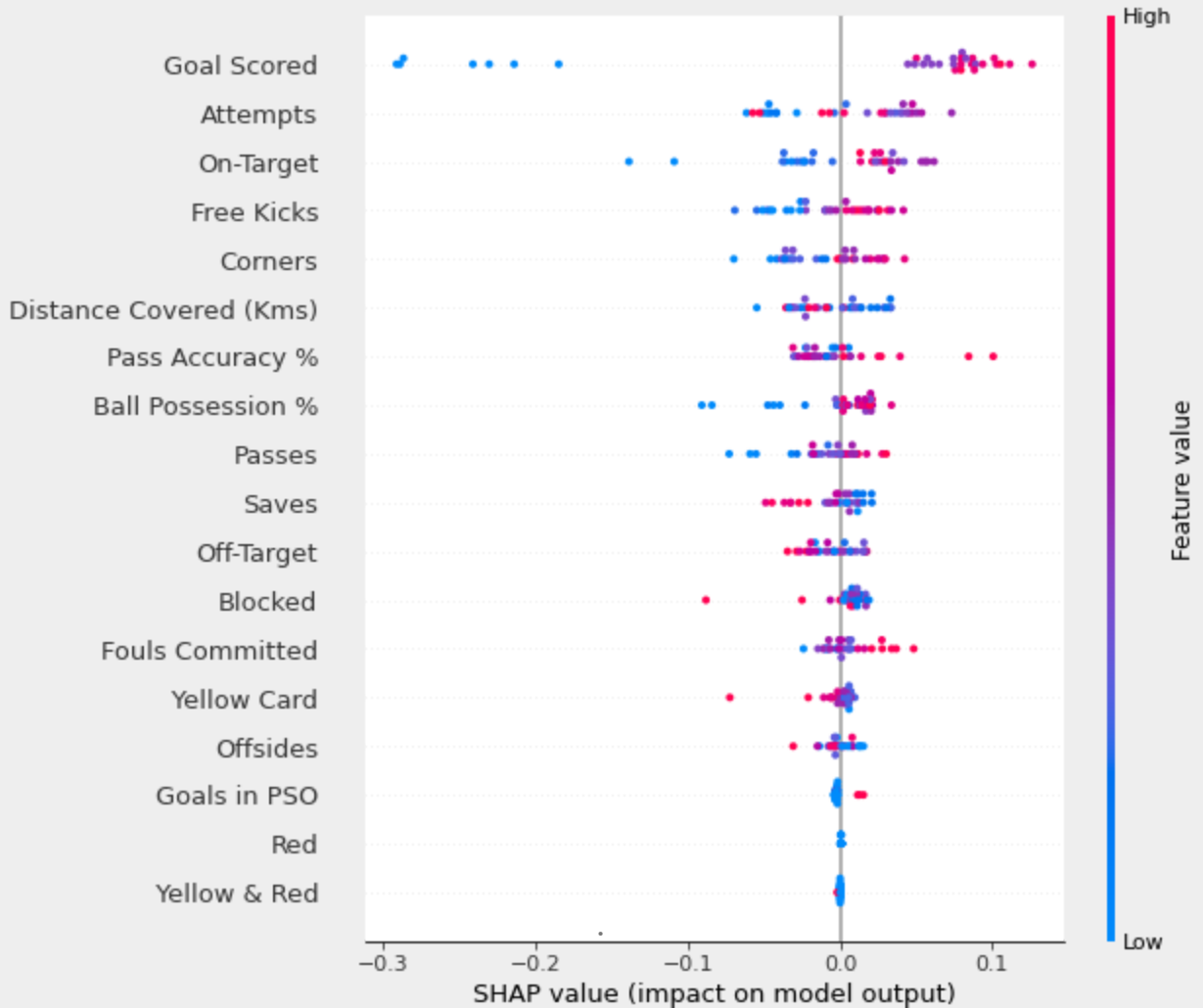
```
from sklearn.dummy import DummyClassifier

dummy_clf = DummyClassifier()
dummy_clf.fit(X, y)

dummy_clf.score(X, y)
```

The simplest of baselines.

Machine Learning Explainability

Statistical methods to explain black box models.

Machine Learning Explainability



Machine Learning Explainability

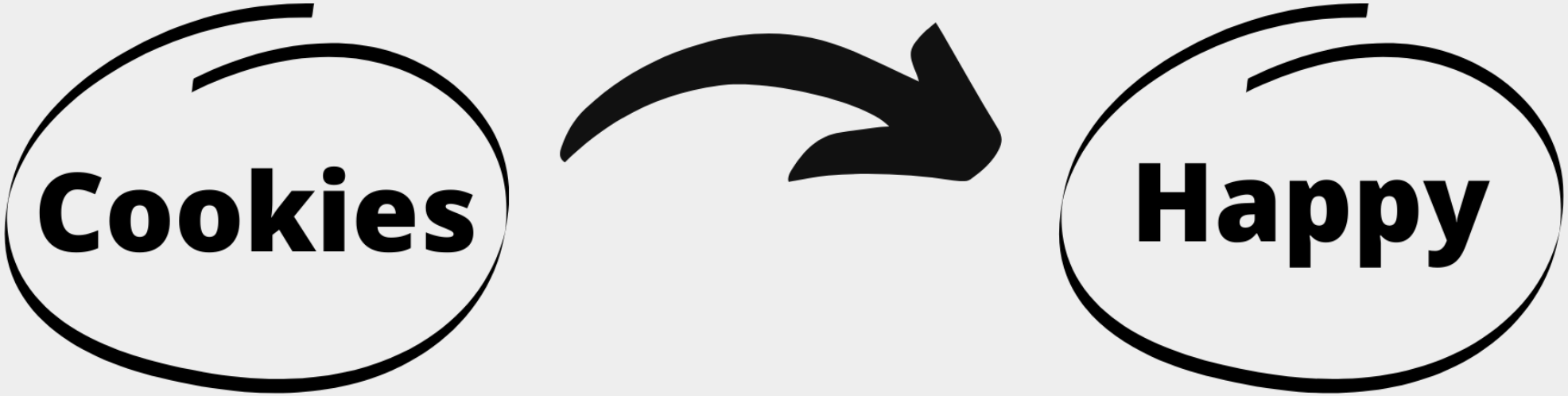
```
import shap
from sklearn.ensemble import RandomForestClassifier
[...]
train_X, val_X, train_y, val_y = train_test_split(X, y)
my_model = RandomForestClassifier().fit(train_X, train_y)

explainer = shap.TreeExplainer(my_model)
shap_values = explainer.shap_values(val_X)
shap.summary_plot(shap_values[1], val_X)
```

[Shap]

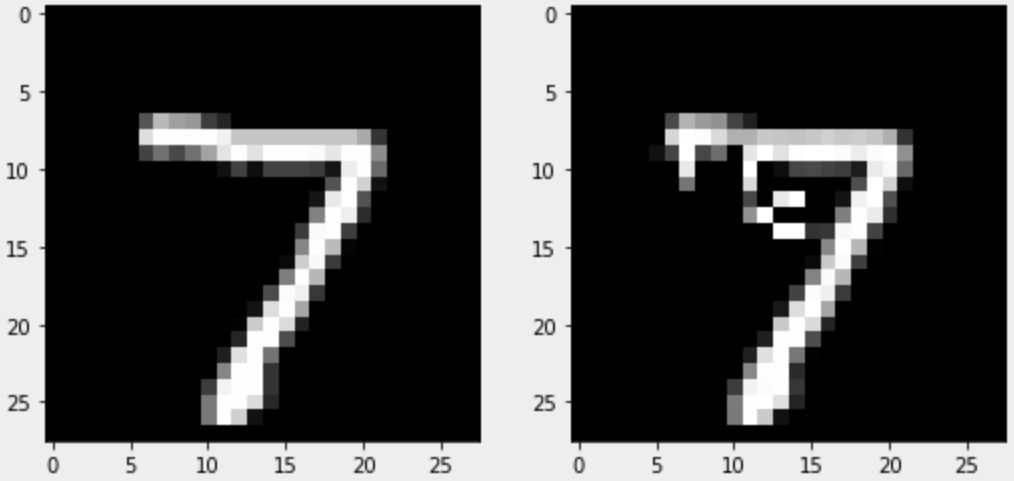
Causality

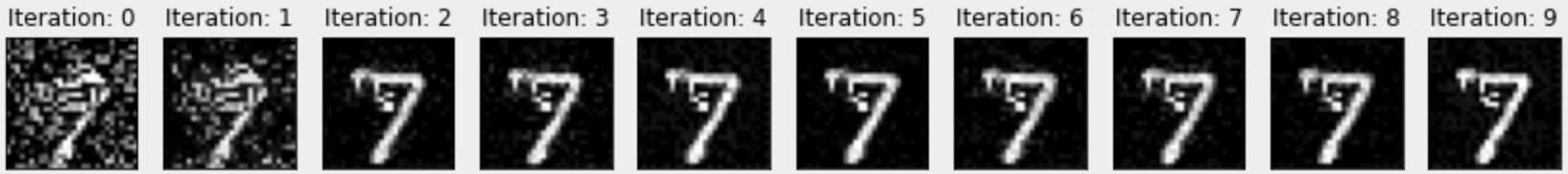
Going beyond correlation

Causality



Causality





[Alibi]

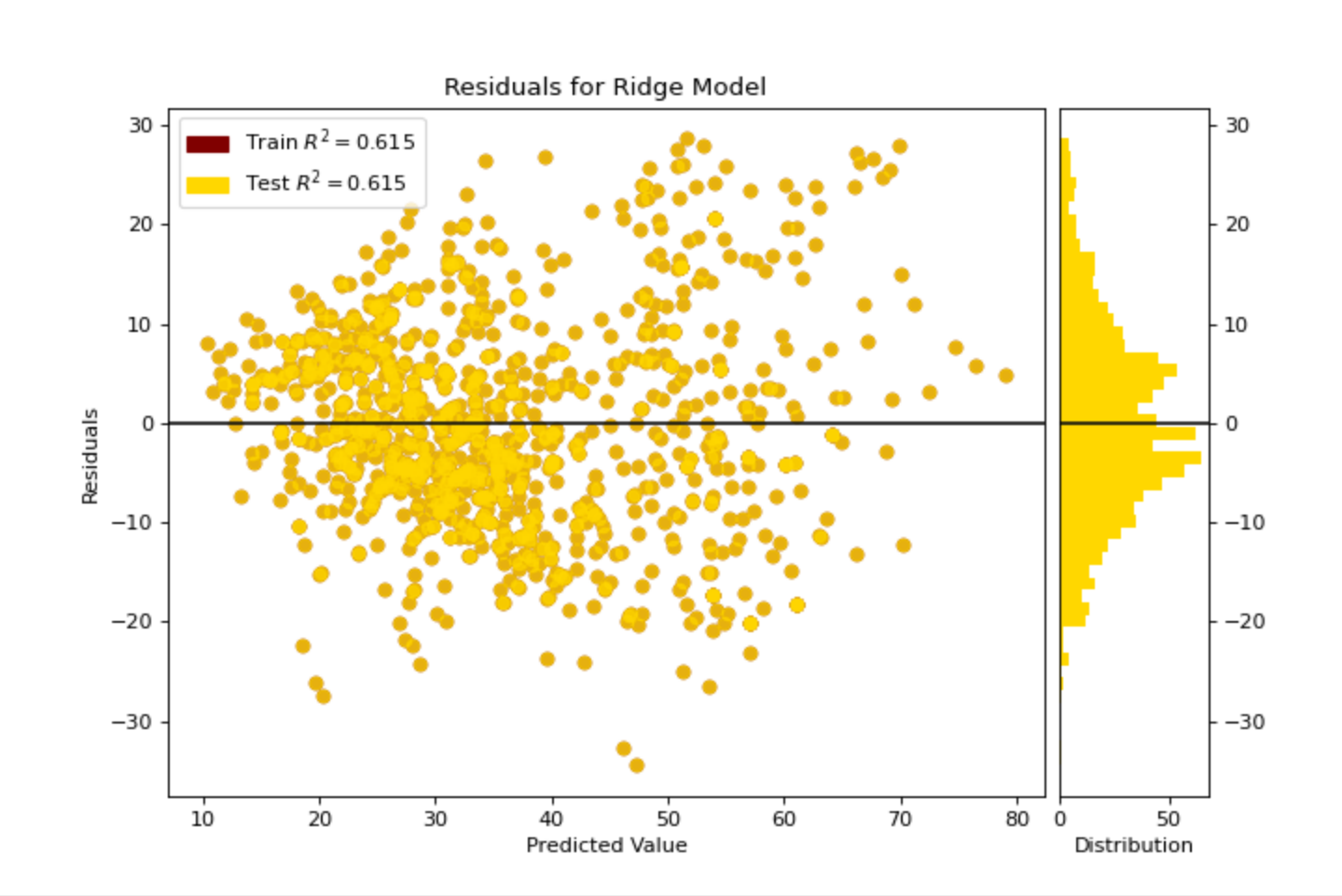
Causality: Counterfactuals

```
from alibi.explainers import Counterfactual
[...]
cnn = Model(inputs=x_in, outputs=x_out)
[...]
X = x_test[0].reshape((1,) + x_test[0].shape)

cf = Counterfactual(cnn, ...)
explanation = cf.explain(X)

pred_class = explanation.cf['class']
proba = explanation.cf['proba'][0][pred_class]

print(f'Counterfactual prediction: {pred_class}
        with probability {proba}')
```

Visualizations

Abstracting information easily digestible and intuitive

Helpful Visualizations



Helpful Visualizations

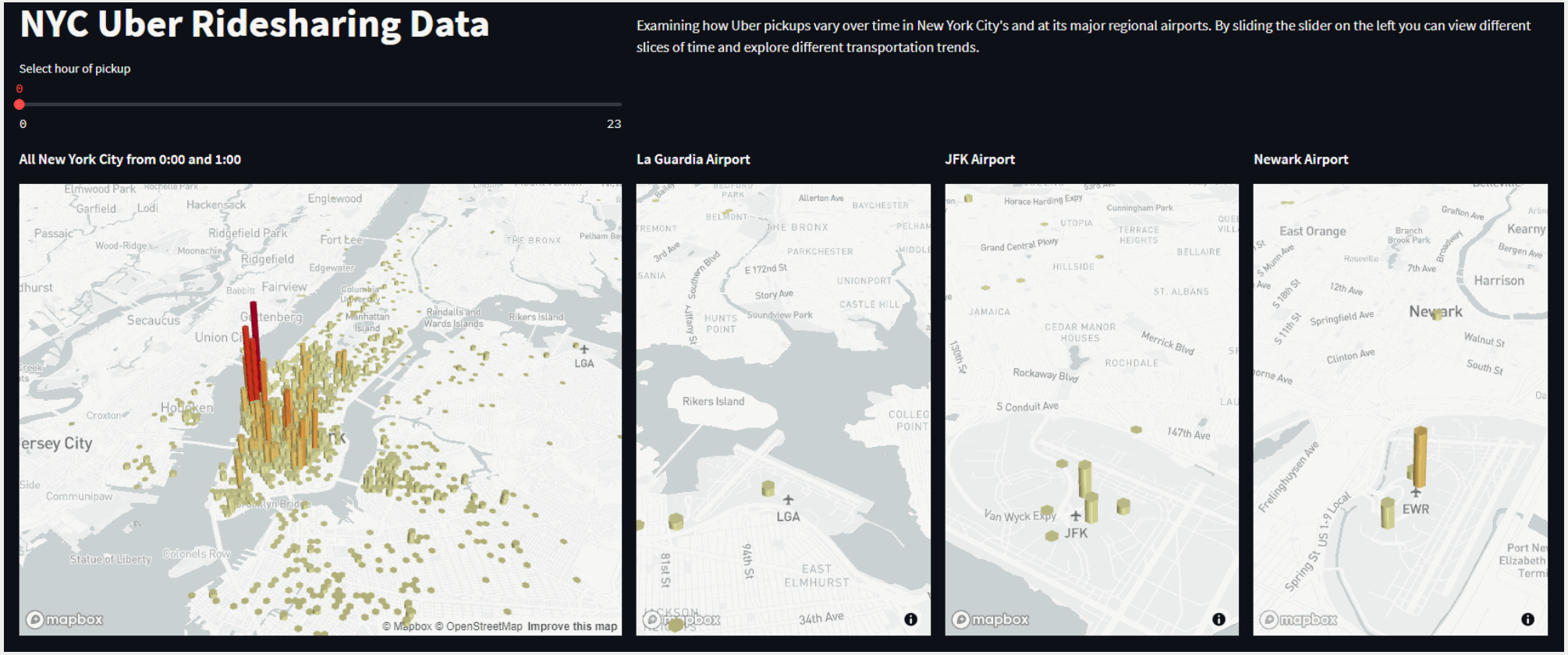
```
from sklearn.linear_model import Ridge
from yellowbrick.datasets import load_concrete
from yellowbrick.regressor import residuals_plot


X, y = load_concrete()
visualizer = residuals_plot(
    Ridge(), X, y, train_color="maroon", test_color="gold"
)
```

[Yellowbrick]

Interactivity

Enabling stakeholders to explore data
&
come to the conclusions themselves

Tools for Interactivity



[Streamlit]

Streamlit

Tools for Interactivity

```
import streamlit as st
st.title("NYC Uber Ridesharing Data")
hour_selected = st.slider("Select hour of pickup", 0, 23)

def map(data, lat, lon, zoom):
    st.write(pdk.Deck(
        map_style="mapbox://styles/mapbox/light-v9",
        initial_view_state={ "latitude": lat, "longitude": lon,
            "zoom": zoom, "pitch": 50,},
        layers=[
            pdk.Layer(
                "HexagonLayer", data=data, get_position=["lon", "lat"],
                radius=100, elevation_scale=4, elevation_range=[0, 1000],
                pickable=True, extruded=True, ),]))
```

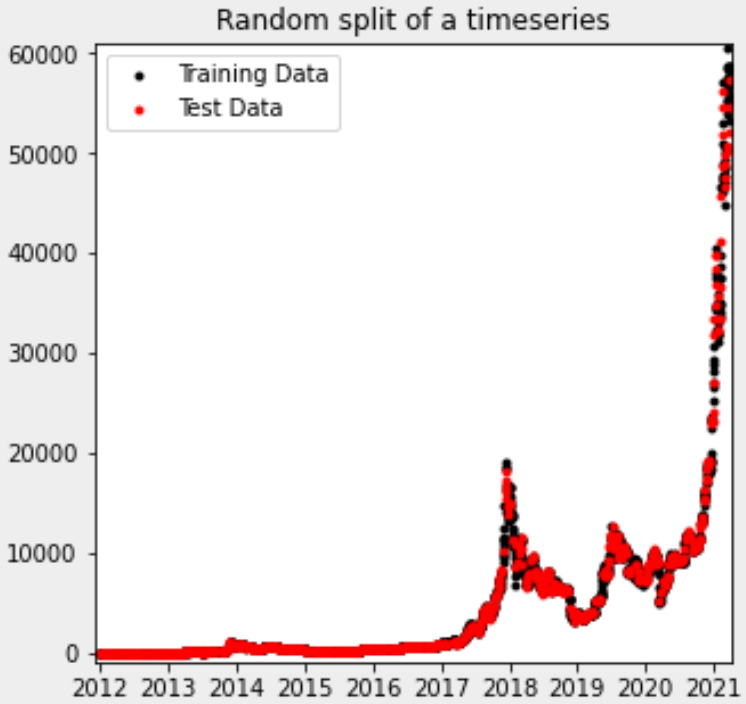
Model Validation

Experts know how difficult their data is to work with

Specific Model Validation

- Time Series
- Geospatial Data
- Spatiotemporal Data
- Online Learning

Specific Model Validation: Time Series

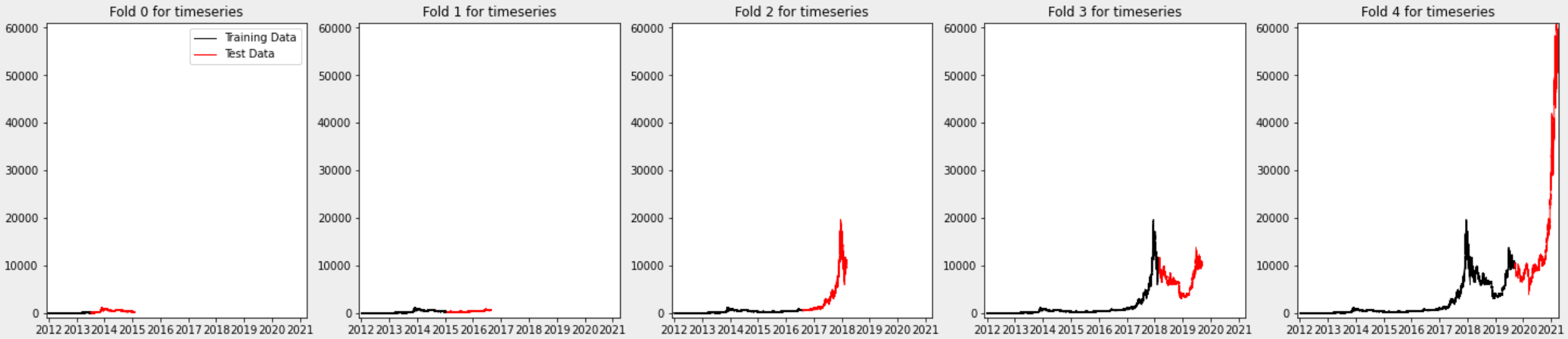


- A time series is correlated in time

```
from sklearn.model_selection import train_test_split
train, test = train_test_split(data)
```

- Random split not suitable
- Time-series validation

Specific Model Validation: Time Series



Use "future" samples for validation.

Specific Model Validation: Time Series

```
from sklearn.model_selection import TimeSeriesSplit

tscv = TimeSeriesSplit()

for i, (train_index, val_index) in enumerate(tscv.split(data)):
    model.fit(data[train_index])
    model.score(data[val_index])
```

Special methods for correlated data

Conclusion

- Build trust is important
- Follow domain expert advice
- Your model isn't that important
- Build baseline models
- Use visualizations and interactive dashboard
- Many tools that help communicate machine learning
- Carefully consider validation