ML for SS: Bias

Session 10

Dr. Richard M. Crowley
rcrowley@smu.edu.sg
http://rmc.link/

Overview

Papers

- Wich, Bauer and Groh (2020)
  - A paper using SHAP to understand an impact of political bias
- Lundberg et al. (2018)
  - A practical use of SHAP for model explainability
  - The team behind this paper contains the team from the original SHAP paper (Lundberg and Lee (2017))

Technical Discussion

Focus on the SHAP method

Python

- Use the `shap` library
  - By the original author team
  - Great visualization support
  - Decent documentation
  - Has some bugs
  - Sometimes you need to use older packages with it

R

- For XGBoost, you can use `SHAPforxgboost`
- For accessing the python package in R, use `shapper`
- For native SHAP, use `shapr`, but it is missing a lot of features

Python's support is a lot better here unless your model is an XGBoost

SHAP

What exactly is SHAP?

> Aims to provide an explanation of the importance of model inputs in explaining model output

- Game theoretic and theory driven
- Unifies six other methods that tried to address this problem
- It is a model itself: a model to explain models
- Provides a simple to understand output

> SHAP: *SH*apley *A*dditive ex*P*lanations

- Based on Shapley, 1953, “A value for n-person games.”
- SHAP itself is from Lundberg and Lee (2017)

Principles of SHAP

1. Local accuracy
    - The simple model is able to accurately predict a model output on small subsets of the data
2. Missingness
    - SHAP only uses data the original model had access to
    - If data was missing from the original model, SHAP won't use it
3. Consistency
    - Akin to transitivity conditions in utility theory (Savage Axioms)
        - But instead of "utility," we have "simplified model's input's contribution"

SHAP in more detail

> SHAP is, per Lundberg and Lee (2017), the unique solution that maintains local accuracy and consistent from a class of methods called *additive feature attribution methods* (AFAM)

AFAM's have a linear function of binary variables where $z' \in \{0,1\}^M$ where M is a number of simplified input features and $\phi_i \in \mathbb{R}$, $x = h_x(x')$, and $g(z') \approx f(h_x(z'))$ when $z' \approx x'$.

$$g(z') = \phi_0 + \sum_{i=1}^{M} \phi_i z_i'$$

- 6 other methods in the literature also fit in the class
  - LIME, DeepLIFT, Layer-Wise Relevance Propagation, Shapley regression values, Shapleu sampling values, Quantitative input influence
  - These methods were approximating SHAP

SHAP: Local accuracy

$$f(x) = g(x') = \phi_0 + \sum_{i=1}^{M} \phi_i x'_i$$

- $g(x')$ is the explanation model of $f(x)$ where $x = h_x(x')$ and $\phi_0 = f(h_x(0))$

> Not all other methods have this

SHAP: Missingness

$$x'_i = 0 \Rightarrow \phi_i = 0$$

- “Features missing in the original input [have] no impact”

All AFAM models have this

SHAP: Consistency

Let $f_x(z') = f(h_x(z'))$ and $z' \backslash i$ denote setting $z'_i = 0$. For any two models f and f':

$$f'_x(z') - f'_x(z' \backslash i) \geq f_x(z') - f_x(z' \backslash i) \quad \forall z' \in \{0,1\}^M \Rightarrow \phi_i(f', x) \geq \phi_i(f, x)$$

- Recall that ϕ is measuring feature importance of i
- If removing i drops the prediction more under f'_x than under f_x, then it has more feature importance under f'_x than under f_x

> Not all other methods have this

SHAP: The solution

$$\phi_i(f,x) = \sum_{z' \subseteq x'} \frac{|z'|!(M-|z'|-1)!}{M!}[f_x(z') - f_x(z'\backslash i)]$$

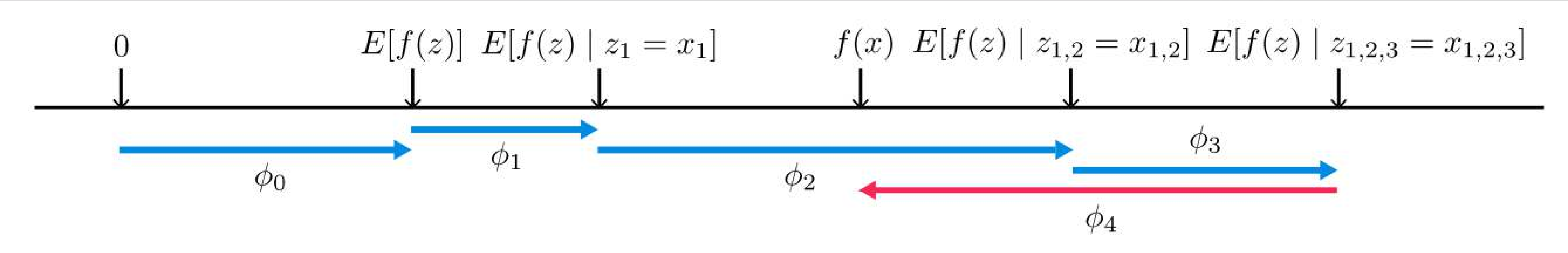
- Where:
  - $|z'|$ is the number of non-zero entries in z'
  - $z' \subseteq x'$ is the set of all z' s.t. the non-zero entries are a subset of the non-zero entries in x'

> Combinatoric weighting to the difference element i adds to f_x

> SHAP sets $f_x(z') = f(h_x(z')) = (E)[f(z)|z_S]$; S is the set of non-zero indees in z'

- Then approximate it all

Intuition of SHAP



- SHAP is defined by a series of [conditional] expectation of the impact of an input
- For linear models, order of selecting inputs has no effect
- For nonlinear models, SHAP averages inputs’ conditional expected impact over all possible orderings
  - This is computationally intensive on high-dimensional data

Prepping SHAP

An example of quantifying bias

- Data: City of Chicago salaries
  - 33,586 employees
- Trained using a simple XGBoost model
- Features:
  - Job title
  - Department
  - Full time / part time
  - Salaried or hourly
  - Female

> Is there gender bias in annual compensation?

The data

```python
vars = ['Job.Titles', 'Department', 'Full.Time', 'Salaried', 'Female']
df[vars]
```

```
##                                Job.Titles        Department  Full.Time  \
## 0                                SERGEANT            POLICE          1
## 1      POLICE OFFICER (ASSIGNED AS DETECTIVE)        POLICE          1
## 2                                   Other  GENERAL SERVICES          1
## 3                                   Other       WATER MGMNT          1
## 4                                   Other        TRANSPORTN          1
## ...                                   ...               ...        ...
## 33581                      POLICE OFFICER            POLICE          1
## 33582                      POLICE OFFICER            POLICE          1
## 33583                      POLICE OFFICER            POLICE          1
## 33584                      POLICE OFFICER            POLICE          1
## 33585                               Other             Other          1
##
##        Salaried  Female
## 0             1     0.0
## 1             1     1.0
## 2             1     1.0
## 3             1     0.0
## 4             0     0.0
## ...         ...     ...
## 33581         1     1.0
```

One hot encoding categorical data

- Pandas has a function for this, `pd.get_dummies()`
  - `prefix=` lets us name the columns of the output
- As `pd.get_dummies()` outputs a new data frame only containing the new columns, we need to join them back
  - `df.join()` makes this quick and easy

```python
one_hot1 = pd.get_dummies(df['Job.Titles'], prefix='Job.Titles')
one_hot2 = pd.get_dummies(df['Department'], prefix='Department')

df = df.join(one_hot1)
df = df.join(one_hot2)
```

Prepping XGBoost

We did this in Session 3

```python
vars = one_hot1.columns.tolist() + \
       one_hot2.columns.tolist() + \
       ['Full.Time', 'Salaried', 'Female']
dtrain = xgb.DMatrix(df[vars], label=df['Salary'], feature_names=vars)
```

```python
param = {
    'booster': 'gbtree',              # default -- tree based
    'nthread': 8,                     # number of threads to use for parallel processing
    'objective': 'reg:squarederror', # RMSE error
    'eval_metric': 'rmse',           # maximize ROC AUC
    'eta': 0.3,                      # shrinkage; [0, 1], default 0.3
    'max_depth': 6,                  # maximum depth of each tree; default 6
    'gamma': 0,                      # set above 0 to prune trees, [0, inf], default 0
    'min_child_weight': 1,           # higher leads to more pruning of tress, [0, inf], default 1
    'subsample': 1,                  # Randomly subsample rows if in (0, 1), default 1
}
num_round=30
```

Building our model and prepping SHAP

- We call `xgb.train()` to fit our XGBoost model

```python
model_xgb = xgb.train(param, dtrain, num_round)
```

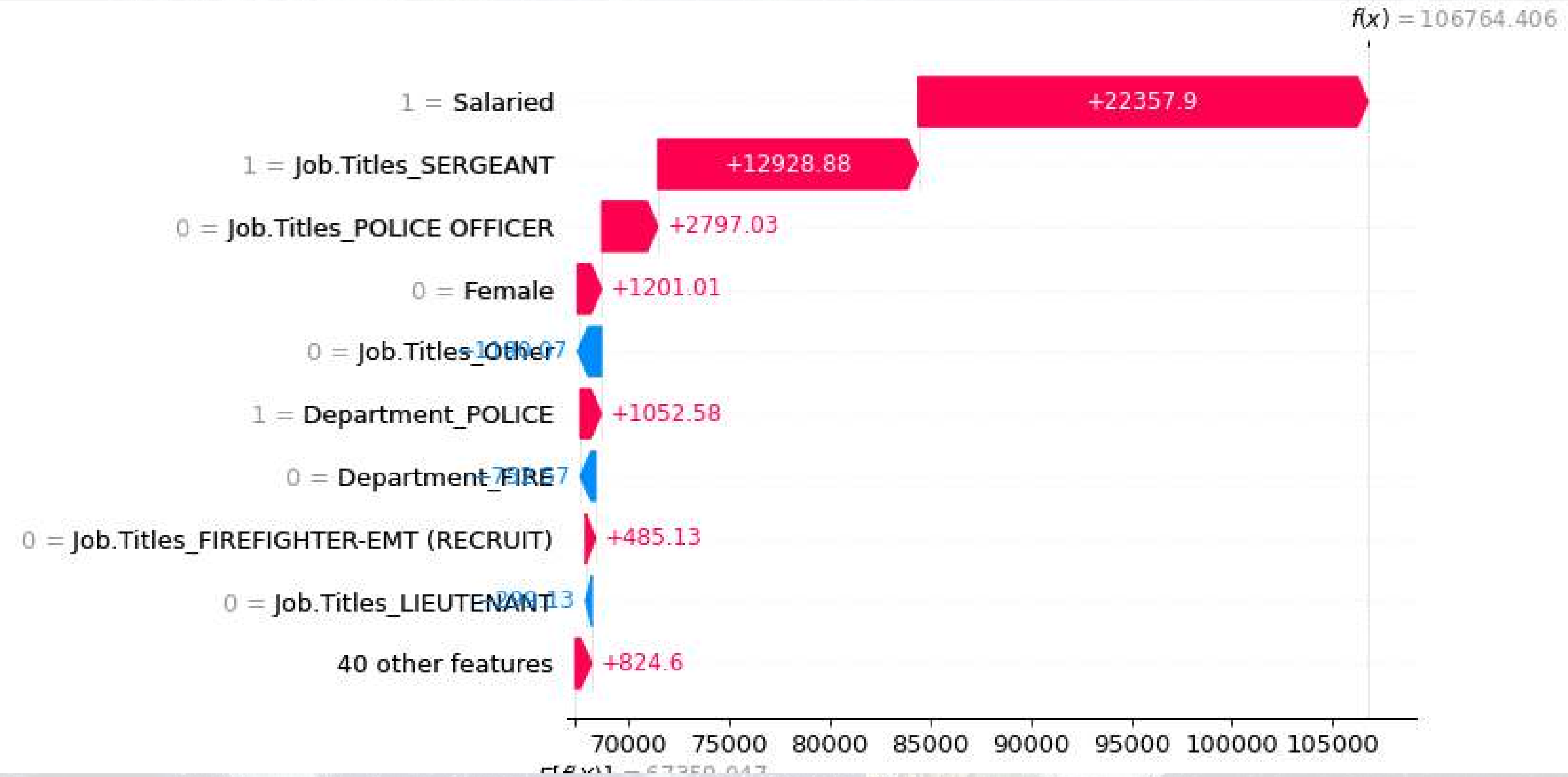
- Since XGBoost is a tree-based model, we will use SHAP's `shap.TreeExplainer()` function to analyze the model
- Since we only have in-sample data, we will compute SHAP on the same data the XGBoost model was fit to
- We will also prepare a small sample for more CPU-intensive analyses

```python
explainer = shap.TreeExplainer(model_xgb)
shap_values = explainer(df[vars])

df_small = df.sample(frac=0.01)
shap_values_small = explainer(df[vars])
```

Explaining a single observation

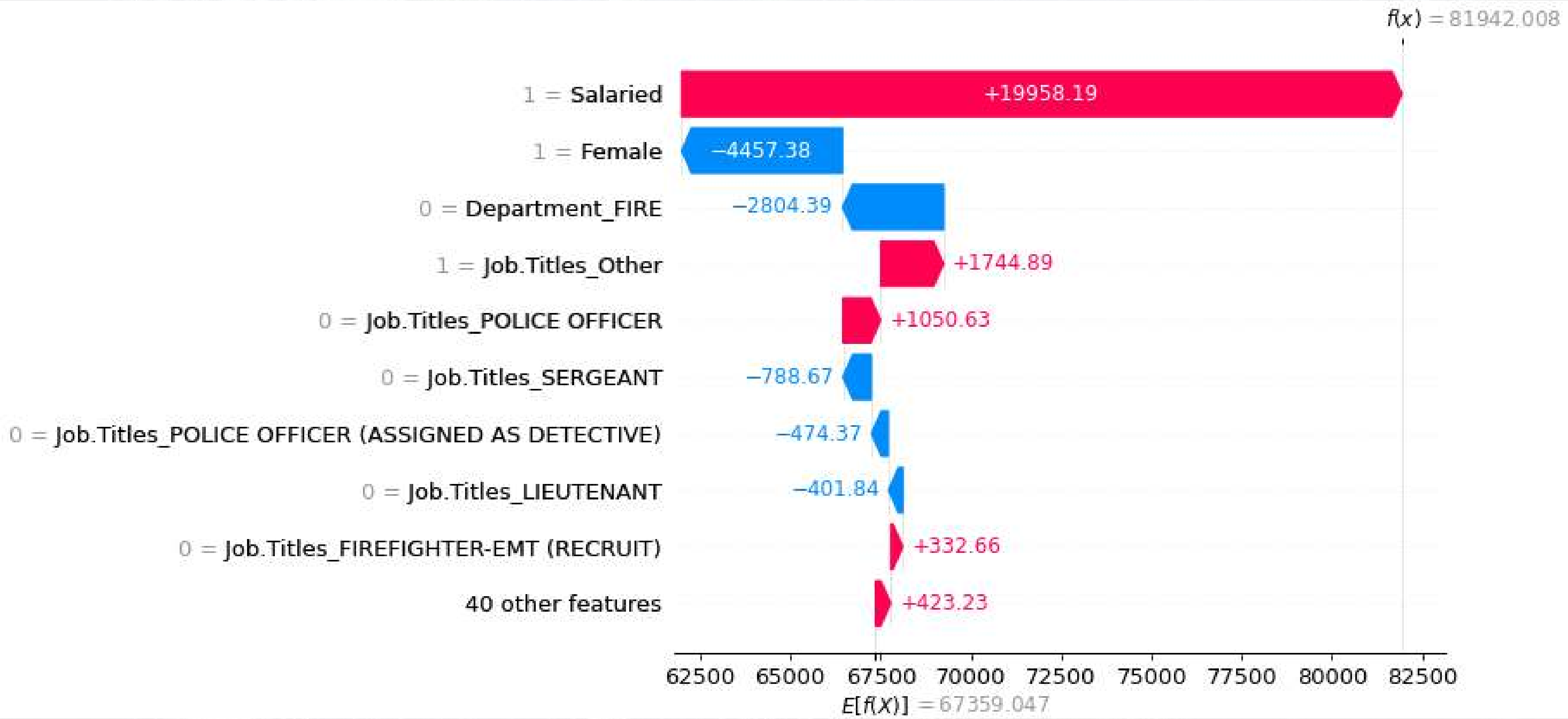
```python
shap.plots.waterfall(shap_values[0])
```



Here we see that having `Female=0` was the fourth most influential feature in the model, and that it led to a *higher* predicted salary

Explaining a single observation

```python
shap.plots.waterfall(shap_values[2])
```

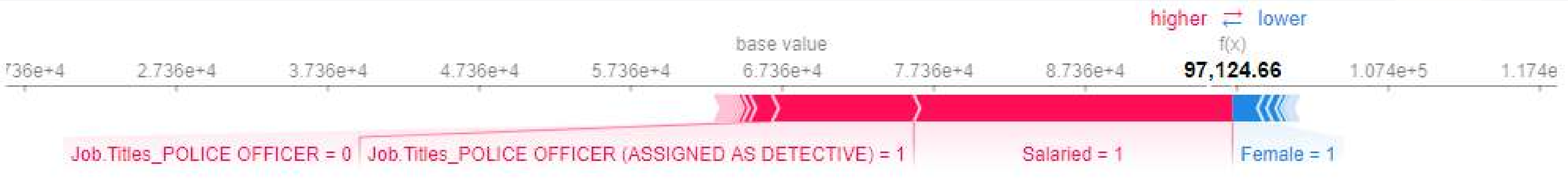


> Here we see that having `Female=1` was the second most influential feature in the model, and that it led to a *lower* predicted salary

Charting with SHAP

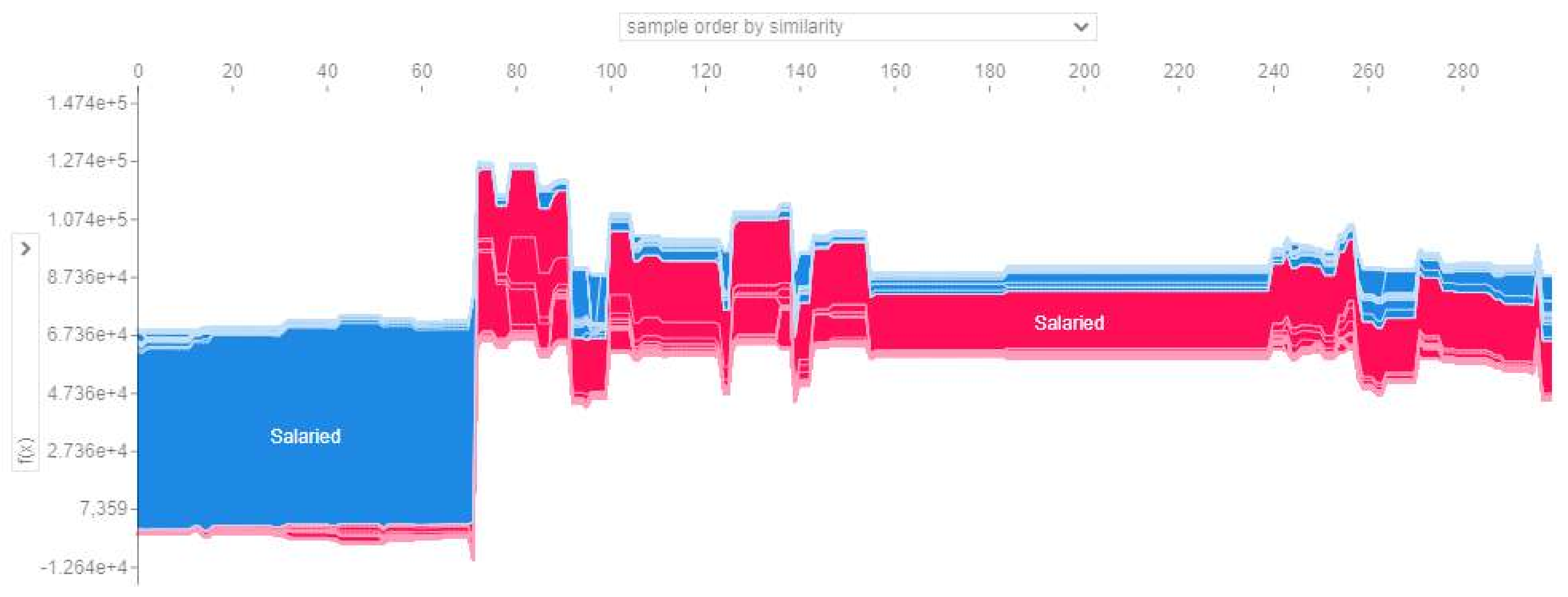
A more concise point visualization

```
shap.plots.force(shap_values[1])
```



Aggregating across the data

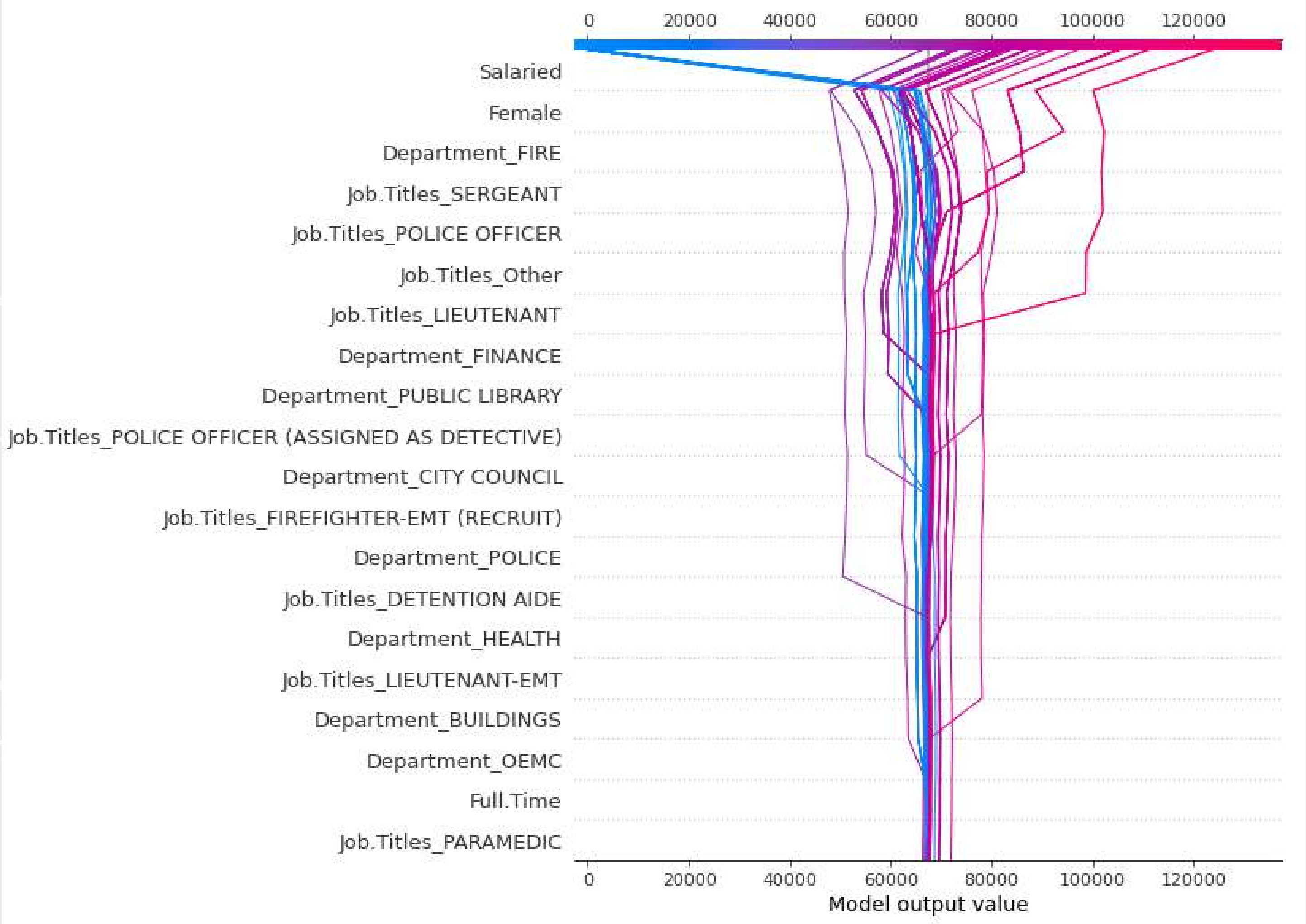
```python
N=300
shap.plots.force(explainer.expected_value, shap_values.sample(N).values, feature_names=vars)
```



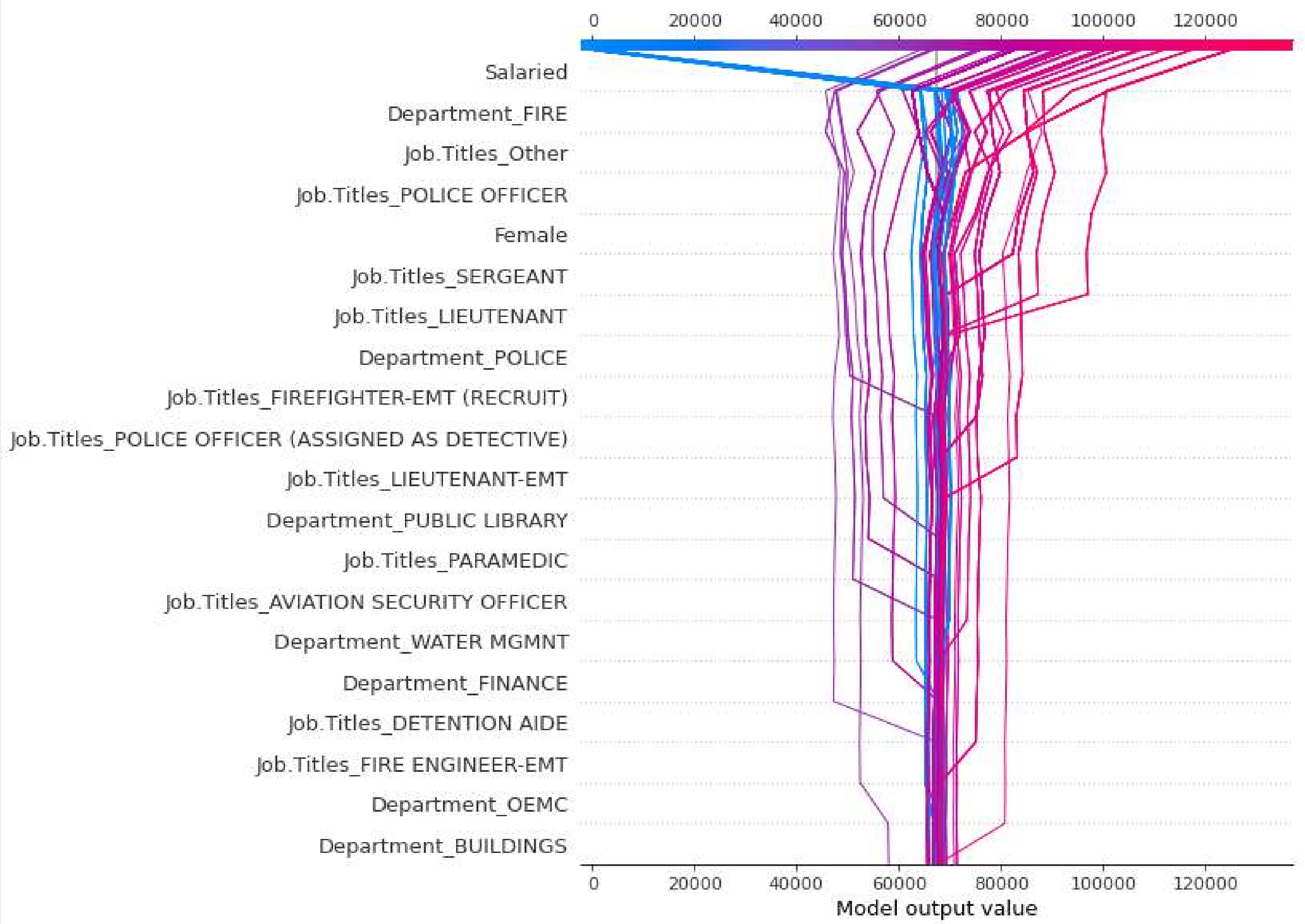
Seeing more variables’ impact

- A “Decision plot” uses a line chart to show the impact of more measures across the data

```python
shap.decision_plot(
  explainer.expected_value,
  explainer.shap_values(df_small[df_small.Female==1][vars
  feature_names=vars)
```



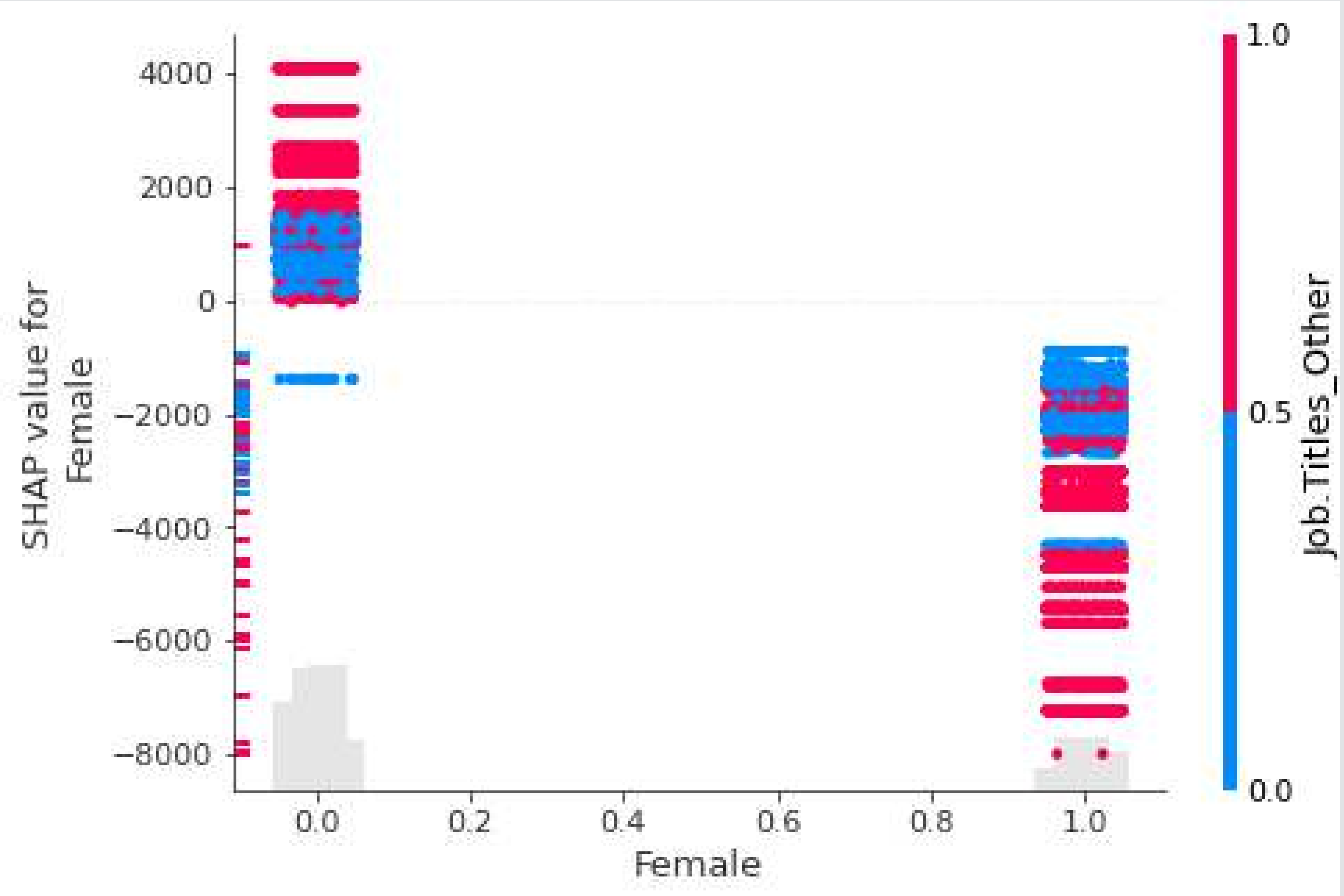

```python
shap.decision_plot(
  explainer.expected_value,
  explainer.shap_values(df_small[df_small.Female==0][vars
  feature_names=vars)
```



Aggregate analysis of an individual variable

- If we want to see the full impact of “Female” on outcomes in our data, a scatter plot is useful

```
shap.plots.scatter(shap_values[:,"Female"], color=shap_values)
```

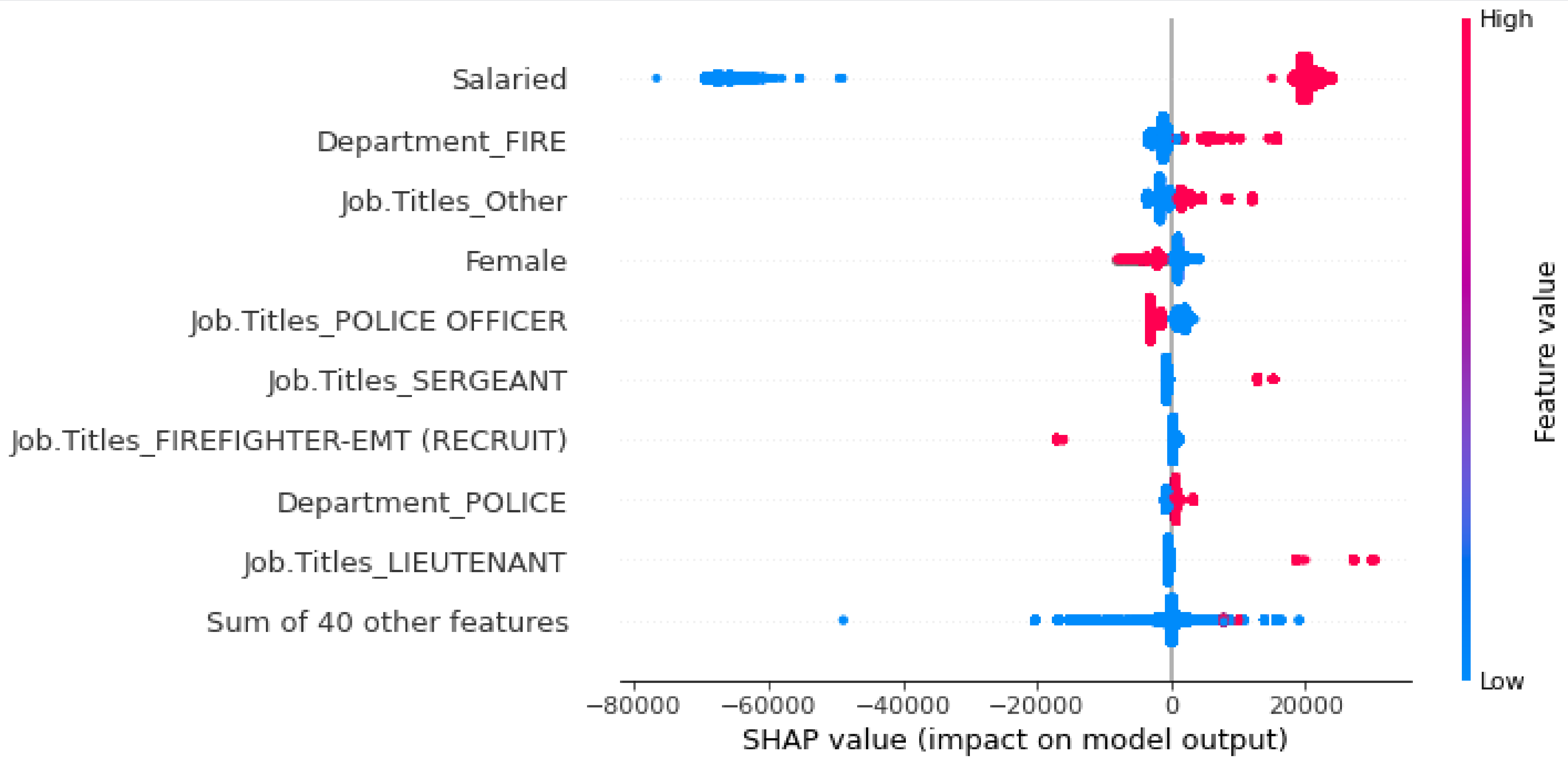


> Remember that our model is nonparametric! Signs can be different even when the variable doesn’t change due to interactive effects

Multiple scatterplots at once: Bee swarm

- If you want a concise way to present multiple variables, the bee swarm plot can be useful

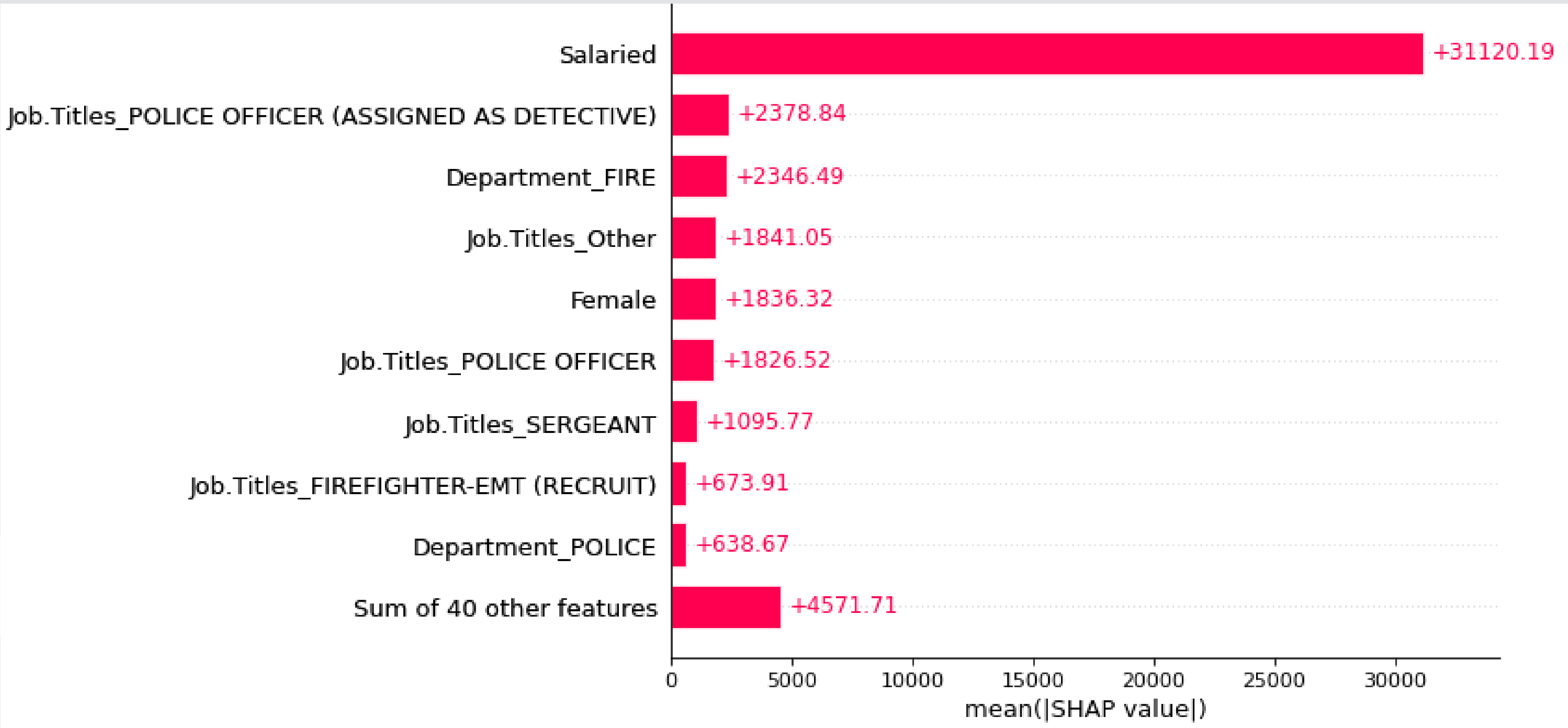
```python
shap.plots.beeswarm(shap_values)
```



Importance plot

- Lastly, we can replicate XGBoost's importance plot using $|\mathrm{SHAP}|$

```python
shap.plots.bar(shap_values)
```



> This may not be useful for XGBoost since it already has an importance metric, but many other models lack it

Addendum: Using R

- If you are working explicitly with XGBoost, there is a great `SHAPforxgboost` package
- To interface with the python `shap` package, you can use `shapper`
- There is also `shapr`, though it isn't as full-featured.

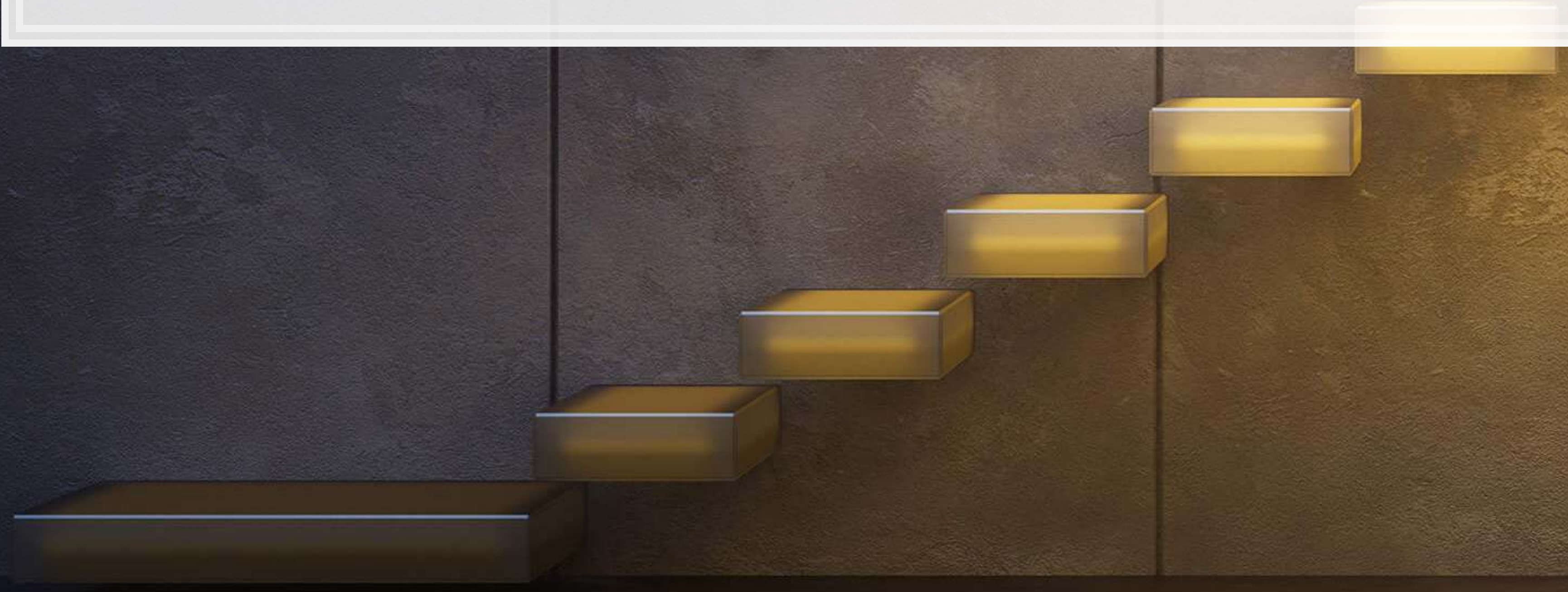
Conclusion

Wrap-up

SHAP can provide some insight into models at the observation, group, and sample level

- For more complex models, this helps to unwrap the “black box” some

SHAP can provide us with [conditional] marginal effects-like analysis for more complex models



Packages used for these slides

Python

- numpy
- pandas
- shap
- xgboost

References

- Lundberg, Scott, and Su-In Lee. “A unified approach to interpreting model predictions.” In Proceedings of the 31st Conference on Neural Information Processing Systems. (2017).
- Lundberg, Scott M., Bala Nair, Monica S. Vavilala, Mayumi Horibe, Michael J. Eisses, Trevor Adams, David E. Liston et al. “Explainable machine-learning predictions for the prevention of hypoxaemia during surgery.” Nature biomedical engineering 2, no. 10 (2018): 749-760.
- Wich, Maximilian, Jan Bauer, and Georg Groh. “Impact of politically biased data on hate speech classification.” In Proceedings of the Fourth Workshop on Online Abuse and Harms, pp. 54-64. 2020.