# STAT 207: Final Project

~ Sarah Michalec - Jada Giddens - Armeen Sultan - Trish Qiu ~

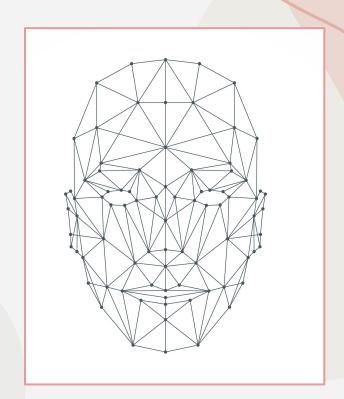
# Motivation and Introduction

#### Research Introduction

- Identity identification and facial recognition
- Equally high accuracy for positives and negative

#### Research Goals

- Primary
  - Build predictive model to predict gender
- Secondary
  - Yield reliable interpretive insights
  - Describe relationship of variables



## **Dataset Discussion**

#### **Dataset Source**

- Retrieved from Kaggle on April 17th, 2024
- Author Jifry Issadeen
- Explanatory variables
  - o 2 Numerical:
    - forehead\_width\_cm
    - forehead\_height\_cm
  - o 5 Categorical:
    - long\_hair
    - nose\_wide
    - nose\_long
    - lips\_thin,
    - distance\_nose\_to\_lip\_long

### **Data Cleaning**

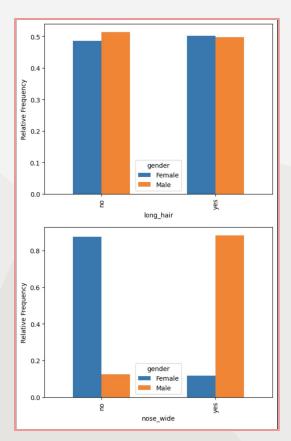
- No implicit or explicit missing values
- No outliers
- Categorical variable counts all >50
- Overall, no rows dropped
  - Model representative of entire dataset

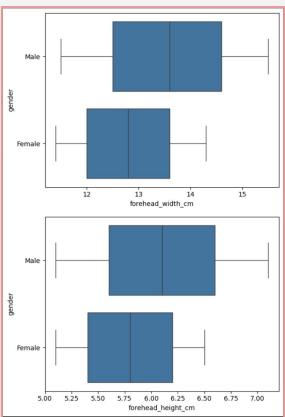


# **Dataset**

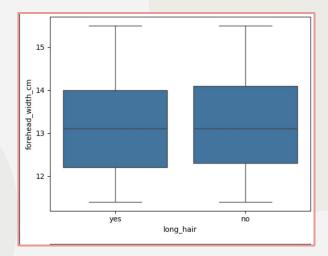
	long_hair	forehead_width_cm	forehead_height_cm	nose_wide	nose_long	lips_thin	distance_nose_to_lip_long	gender
0	1	11.8	6.1	1	0	1	1	Male
1	0	14.0	5.4	0	0	1	0	Female
2	0	11.8	6.3	1	1	1	1	Male
3	0	14.4	6.1	0	1	1	1	Male
4	1	13.5	5.9	0	0	0	0	Female
5	1	13.0	6.8	1	1	1	1	Male
6	1	15.3	6.2	1	1	1	0	Male
7	0	13.0	5.2	0	0	0	0	Female
8	1	11.9	5.4	1	0	1	1	Female
9	1	12.1	5.4	0	0	0	0	Female

# **Descriptive Analytics**

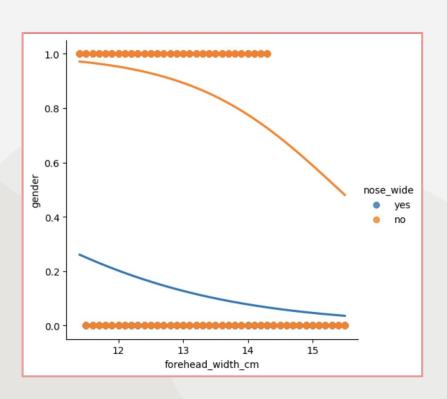




- Long\_hair variable has weak association with response and other explanatory variables.
- Doesn't mean that the variable will under or overfit the model



# **Descriptive Analytics**



- Slope or stretch of the simple logistic model differs
- An interaction term will be made for each pair with an interaction to effectively model the relation between these the explanatory variables and response variable.
- Log likelihood values
  - Full\_model : -368.206
  - Full\_model w/ interaction terms: -363.150

### **Best Model Discussion**

- Tried Lasso, Ridge, Elastic Net Regression
  - 0.996231, 0.996396, 0.996231
  - Ridge model highest AUC

```
gender = rac{1}{ egin{pmatrix} -0.00073589 \ +0.0041852 (\, \mathrm{long\; hair}) \ -0.06137687 (\, \mathrm{forehead\; width\; cm}) \ -0.04974995 (\, \mathrm{forehead\; height\; cm}) \ -0.14924822 (\, \mathrm{nose\; wide}) \ -0.14499015 (\, \mathrm{nose\; long}) \ -0.14275644 (\, \mathrm{lips\; thin}) \ -0.14630999 (\, \mathrm{distance\; nose\; to\; lip\; long}) \ \end{pmatrix}
```

- No slopes zeroed out
  - long\_hair lowest slope
- Probability Threshold: 0.48
  - > FPR: 5%
  - o TPR: 99%
- Multicollinearity
  - Numerical: none
  - Categorical: present
  - Numerical/Categorical: minor
- Cannot interpret slopes
  - Multicollinearity
  - Slope interactions

## Conclusion

- Would recommend our model
  - → High AUC → implies good fit
- Shortcomings
  - Multicollinearity
  - Slope interactions
- Future work
  - Eliminate multicollinearity and slope interactions
  - Test different datasets
    - More explanatory variables

### References

Glover, E. (2024, February 23). Facial Recognition Technology, explained. Built In. <a href="https://builtin.com/articles/facial-recognition-technology-explained#:~:text=Facial%20recognition%20is%20a%20technology.of%20known%20faces%20or%20templates">https://builtin.com/articles/facial-recognition-technology-explained#:~:text=Facial%20recognition%20is%20a%20technology.of%20known%20faces%20or%20templates</a>.

Najibi, A. (2020, October 26). Racial discrimination in face recognition technology. Science in the News. <a href="https://sitn.hms.harvard.edu/flash/2020/racial-discrimination-in-face-recognition-technology/">https://sitn.hms.harvard.edu/flash/2020/racial-discrimination-in-face-recognition-technology/</a>