

PEDESTRIAN IN TRAFFIC

Data Drivers & NSDC



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Our Team

Data Drivers



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The background features a dark blue city street map. Overlaid on the right side of the map is a glowing green outline of a human head in profile, facing right. The text 'ABOUT THE DATA' is centered horizontally across the middle of the image, in a bold, white, sans-serif font.

ABOUT THE DATA

- Multi-agent Pedestrian Tracking (UCI Machine Learning Repository)
 - Multivariate, Sequential, Time-Series
 - 4760 observations x 14 attributes
 - Recorded from a vehicle in southern Germany
- **Our Research Question:** How does the presence & movement of other agents affect the head angle of pedestrians in a given scene?
- Label: head_yaw: yaw head angle in degrees (float)
- Suggested Applications: Autonomous driving, traffic management, urban planning, multi-agent motion prediction



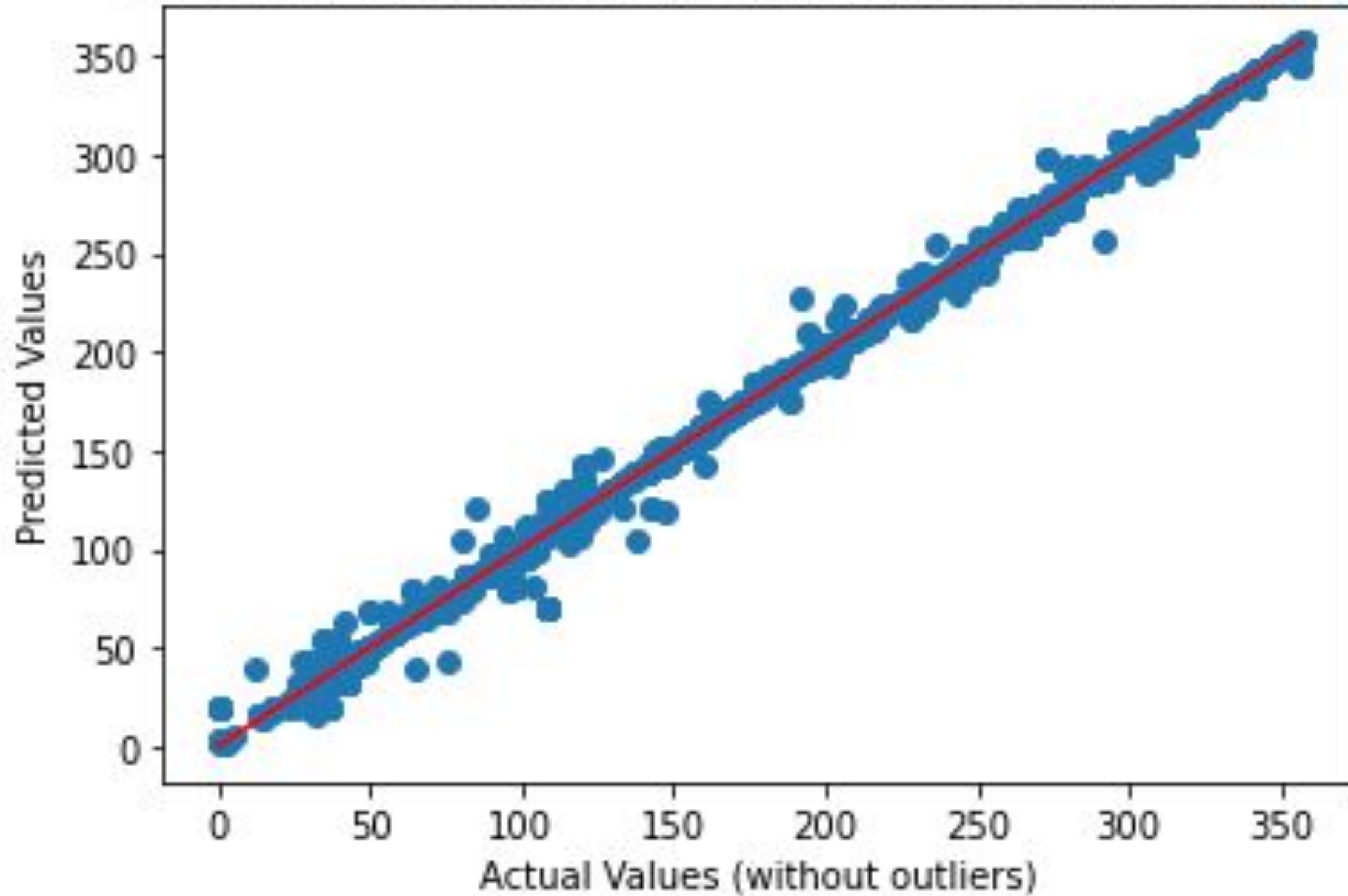
CLEANING THE DATA

- Removal of missing data values for body & head angles
- Exploding coordinate lists for roll, pitch, & yaw for both body & head
- Visualizations of color-coded map with agent information
 - 2D & 3D Scatterplots
 - Heatmaps
 - Box plots
- Feature engineering using polynomial and multivariate regression
 - Linear & logistic regression



OUR PROGRESS

Scatter Plot of Actual vs. Predicted Values (without outliers)



Mean Squared Error (original model): 164.56

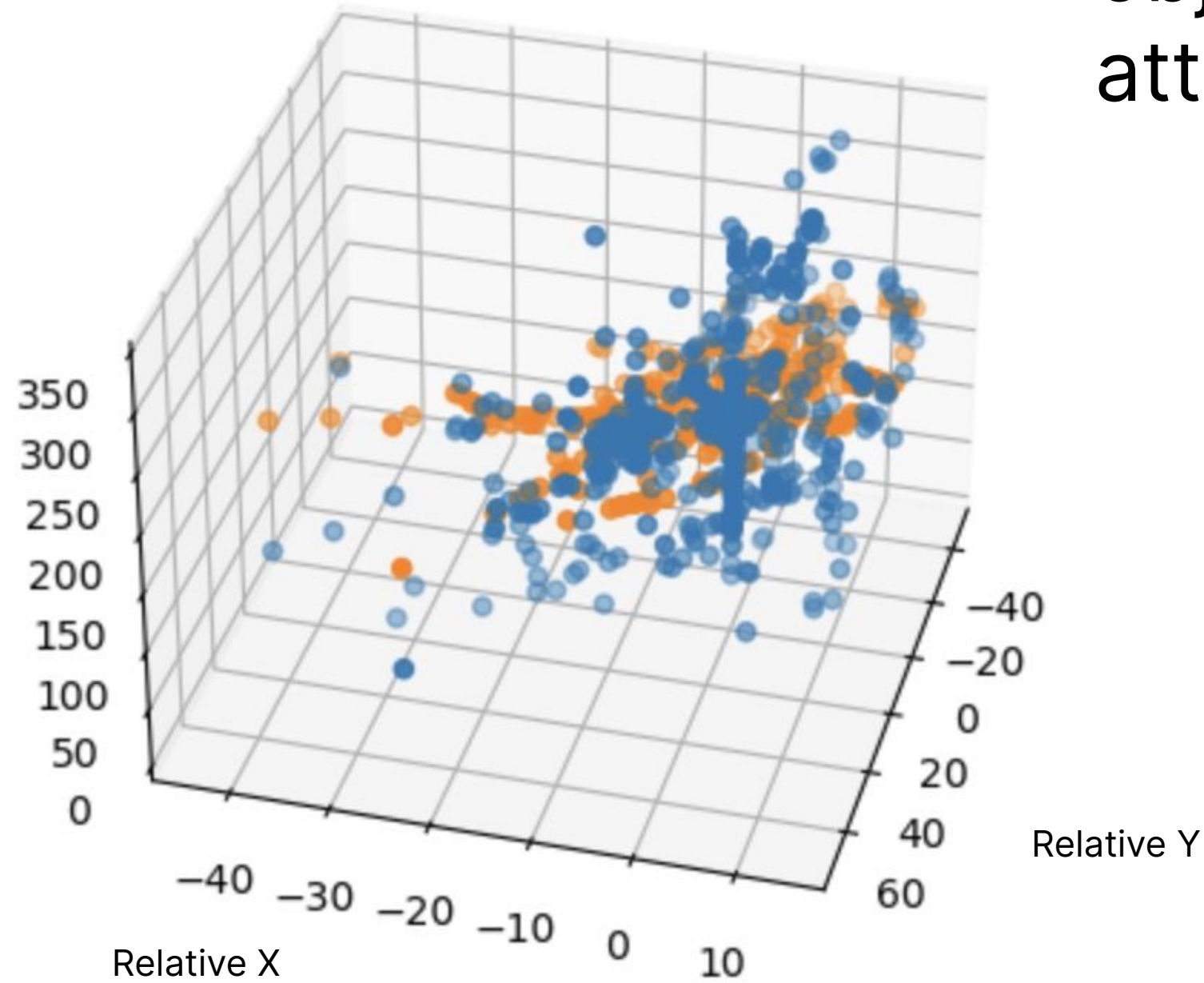
Mean Squared Error (no outliers): 18.67

R Squared (original): 97%

R Squared (no outliers): 99.7%

P values for models created using different classes to determine which object were most likely to grab the attention of the pedestrian

HeadYaw
(Degrees)



$$-0.19504917(\text{relative_x}) - 0.13526806(\text{relative_y}) = \text{headyaw}$$

EGO CAR

```
rel_x      4.360604e-15
rel_y      1.176505e-32
other_class      NaN
headyaw      0.000000e+00
Name: P>|t|, dtype: float64
```

CAR

```
rel_x      0.822146
rel_y      0.000004
other_class      0.920038
headyaw      0.000000
Name: P>|t|, dtype: float64
```

PEDESTRIAN

```
rel_x      1.000000
rel_y      0.000466
other_class      0.004170
headyaw      0.000000
Name: P>|t|, dtype: float64
```



CONCLUSIONS

- **Conclusion:**

- Head angle linked to x-y positions
- High correlation, low R-squared for head angle vs. closest object's position
- Egocars draw most attention, likely due to safety concerns

- **Next Steps:**

- Enhance data collection with advanced sensors and cameras
- Raise public awareness about egocars' impact on pedestrians
- Refine models for improved generalizability

THANK YOU

Data Drivers & NSDC

