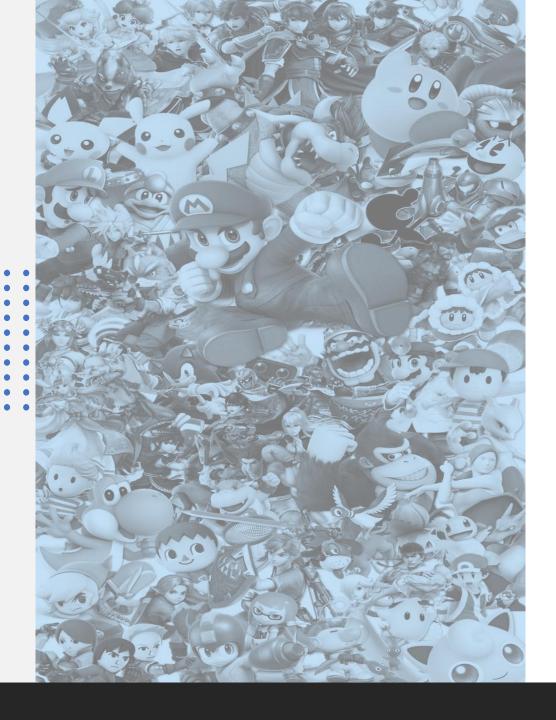


Presentation Layout





Where We Started

Initially started with looking at Videogames

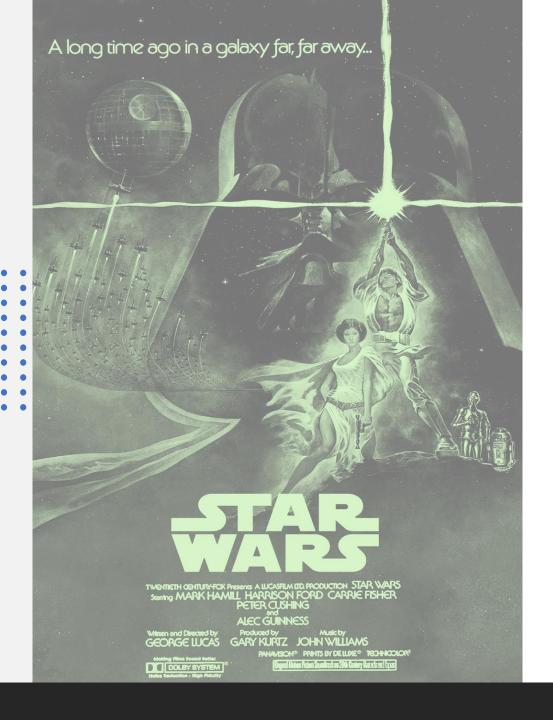
Developer/Publisher/Genre

Then we began exploring potential movie franchises (Fast and Furious, James Bond, Star Wars, etc.)

Franchise performance

Finally, we landed on Marvel/DC – Good/Bad

Characteristics define morality?



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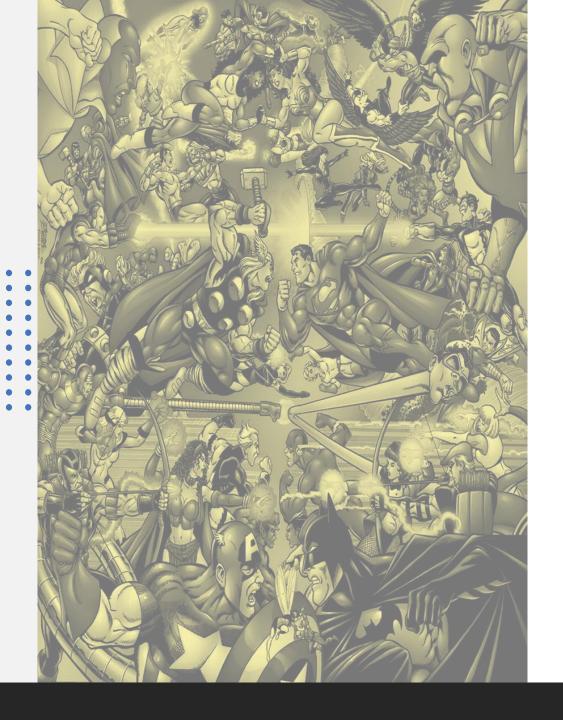
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Characteristics define morality?



Project Focus

Can character traits be an indicator of whether a character is morally "Good" or "Bad"?

Identity

Hair Color

Sex (biological)

Gender/Sexual Preference

Eye Color

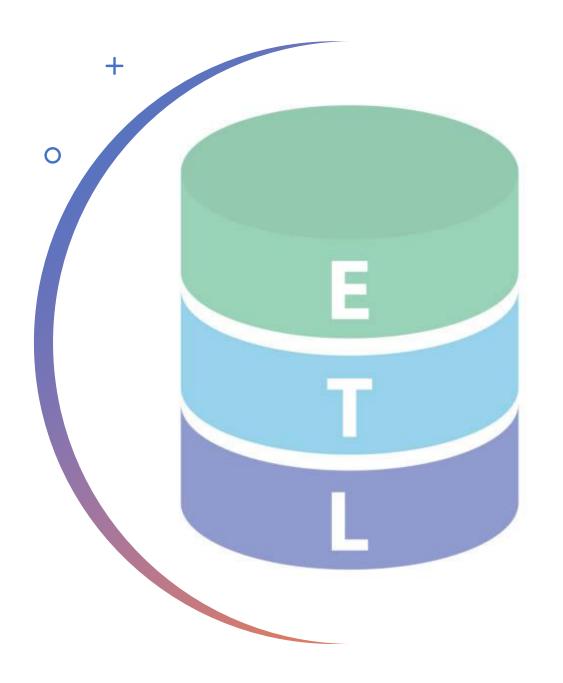
Studio



Data Sources

We utilized 2 datasets found on Kaggle

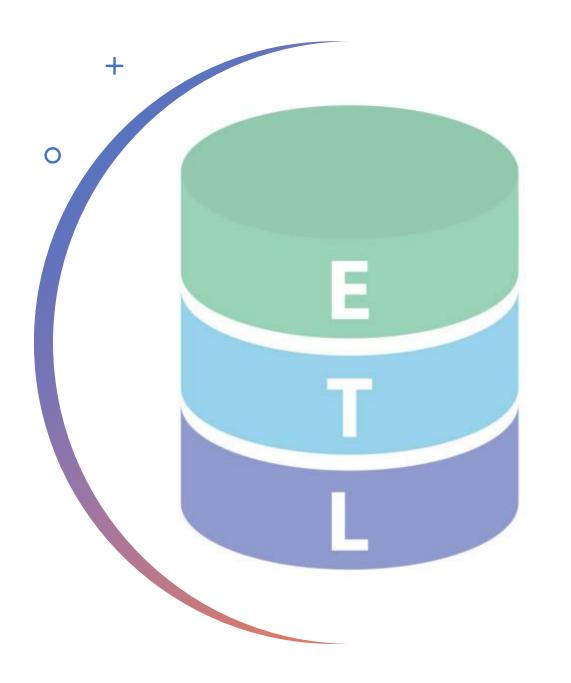
- Marvel-wikia-data.csv
- DC-wikia-data.csv



Extract, Load, Transform

Jupyter Notebook

- Loaded Marvel and DC Kaggle CSVs
- Cleaned datasets
- 3. Added Studio column to differentiate between Marvel vs DC datasets
- 4. Concatenated both datasets into one
- 5. Created SQLAlchemy engine to link pandas dataframe with PostGreSQL



Extract, Load, Transform

Tableau

- Loaded Cleaned CSV
- 2. Edited some of the dimensions
 - 1. Groups, Sets, Re-naming, etc.
- 3. Created Visualizations
- 4. Developed three Dashboards
- 5. Constructed a Story

Data Model Implementation

- Used Google Collab script to:
 - read CSVs
 - convert categorical data to numeric
 - develop ML models
 - Target was 75%
 - Started at 50/50
 - Ended up with ~68%



Data Model Optimization

Predictive Model underperformed on our first attempt.

| Predicting Good, Bad and Neutral Characters | | | | | | | | | |
|---|---|-------|----------|-------------------------------------|----------|--|--|--|--|
| ML Models | • | Score | T | Scaled | Score2 ✓ | | | | |
| Logistic Regression Trainin | g | 56.22 | % | Logistic Regression Training Scaled | 56.36% | | | | |
| Logistic Regression Test | | 54.99 | % | Logistic Regression Test Scaled | 54.97% | | | | |
| Random Forest Training | | 59.60 | % | Random Forest Training Scaled | 59.60% | | | | |
| Random Forest Test | | 54.90 | % | Random Forest Test Scaled | 54.90% | | | | |
| Decision Tree Training | | 59.60 | % | Decision Tree Training Scaled | 59.60% | | | | |
| Decision Tree Test | | 54.62 | % | Decision Tree Test Scaled | 54.62% | | | | |
| Extra Trees Training | | 59.60 | % | Extra Trees Training Scaled | 59.60% | | | | |
| Extra Trees Test | | 54.75 | % | Extra Trees Test Scaled | 54.75% | | | | |
| Ada Boost Training | | 47.86 | % | Ada Boost Training Scaled | 47.86% | | | | |
| Ada Boost Test | | 46.87 | % | Ada Boost Test Scaled | 46.87% | | | | |

Data Model Optimization

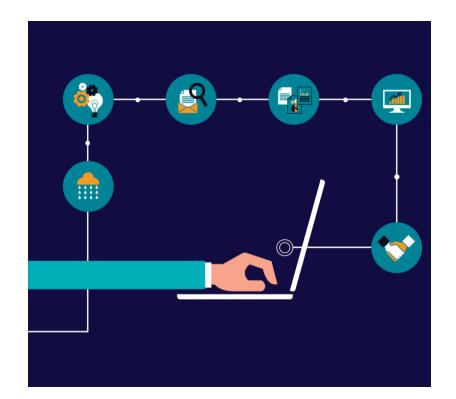
On our second attempt, the model provided much stronger Predictive Validity.

| Predicting Only Good and Bad Characters | | | | | | | | | | |
|---|---|-------|----|-------------------------------------|---|--------|----|--|--|--|
| ML Models | ~ | Score | ~ | Scaled | • | Score2 | | | | |
| Logistic Regression Training | | 65.18 | 3% | Logistic Regression Training Scaled | | 65.1 | 9% | | | |
| Logistic Regression Test | | 64.60 |)% | Logistic Regression Test Scaled | | 64.5 | 7% | | | |
| Random Forest Training | | 68.22 | 2% | Random Forest Training Scaled | | 68.2 | 2% | | | |
| Random Forest Test | | 63.96 | 5% | Random Forest Test Scaled | | 63.9 | 6% | | | |
| Decision Tree Training | | 68.22 | 2% | Decision Tree Training Scaled | | 68.2 | 2% | | | |
| Decision Tree Test | | 63.98 | 3% | Decision Tree Test Scaled | | 63.9 | 8% | | | |
| Extra Trees Training | | 68.22 | 2% | Extra Trees Training Scaled | | 68.2 | 2% | | | |
| Extra Trees Test | | 63.85 | 5% | Extra Trees Test Scaled | | 63.8 | 5% | | | |
| Ada Boost Training | | 59.00 | 0% | Ada Boost Training Scaled | | 59.0 | 0% | | | |
| Ada Boost Test | | 58.52 | 2% | Ada Boost Test Scaled | | 58.5 | 2% | | | |

Results

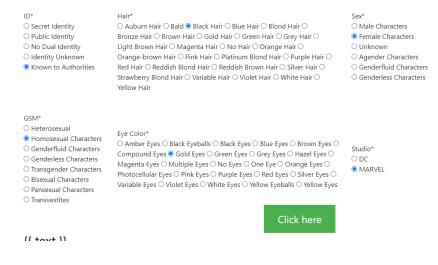
- We can conclude that certain characteristics are somewhat (68%) predictive of a comicbook character's moral compass
- Specific traits lean one way or another
- GSM was the most important feature within the Random Forest model

```
features = sorted(zip(X.columns, rfclf.feature_importances_), key = lambda x: x[1])
cols = [f[0] for f in features]
width = [f[1] for f in features]
fig, ax = plt.subplots()
ax.barh(y=cols, width=width)
plt.show()
   GSM
   SEX
   HAIR
    EYE :
 STUDIO
             0.02
                      0.04
     0.00
                              0.06
                                      0.08
                                              0.10
```



Are you a good or bad character in the Marvel / DC Universe?

Make your selections below, then press the button to find out.



Web Form Using Flask

- Create API from the Postgres database
- Pass form inputs through app using for loop
- Pickle ML model



Limitations



TIME



ACCESS TO SPECIFIC DATASETS



PREDICTIVE
MODELLING BASED ON
STRING DATA
PROVIDES ADDITIONAL
CHALLENGES



NEW SOFTWARE/PACKAGES WE WERE PREVIOUSLY UNAWARE OF (.PKL)



Questions?