WHY PHARMACIES ARE DISAPPEARING IN SAN FRANCISCO

BACKGROUND

The San Francisco Standard

Deserted: 65K San Franciscans to be left without a local pharmacy

When Walgreens closes a dozen stores in February, the Bayview Hunters Point and Ingleside communities will each be stripped of their last remaining pharmacy.

SFGATE

Wave of Walgreens stores to abruptly shutter across San Francisco

A dozen Walgreens stores are slated to shutter across the city of San Francisco at the end of February, spokesperson Marty Maloney confirmed to SFGATE on...

TheStreet

Another pharmacy chain closes stores, no bankruptcy planned

Pharmacies used to be an essential part of the community. They have evolved over the decades and no longer offer soda fountains or food,...

19 hours ago


12 WALGREENS STORES TO CLOSE
80
101
280

WHY THE INDEPENDENTS DISAPPEARED

01

CRIME RATES

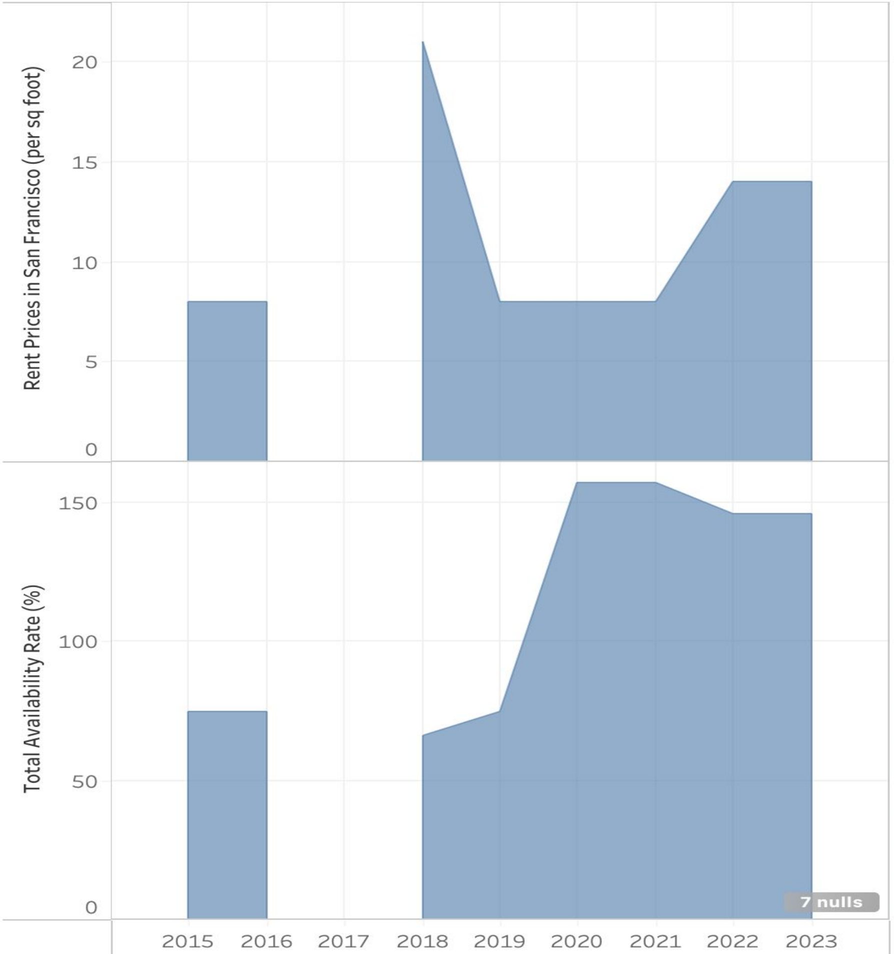
02

RENT PRICES

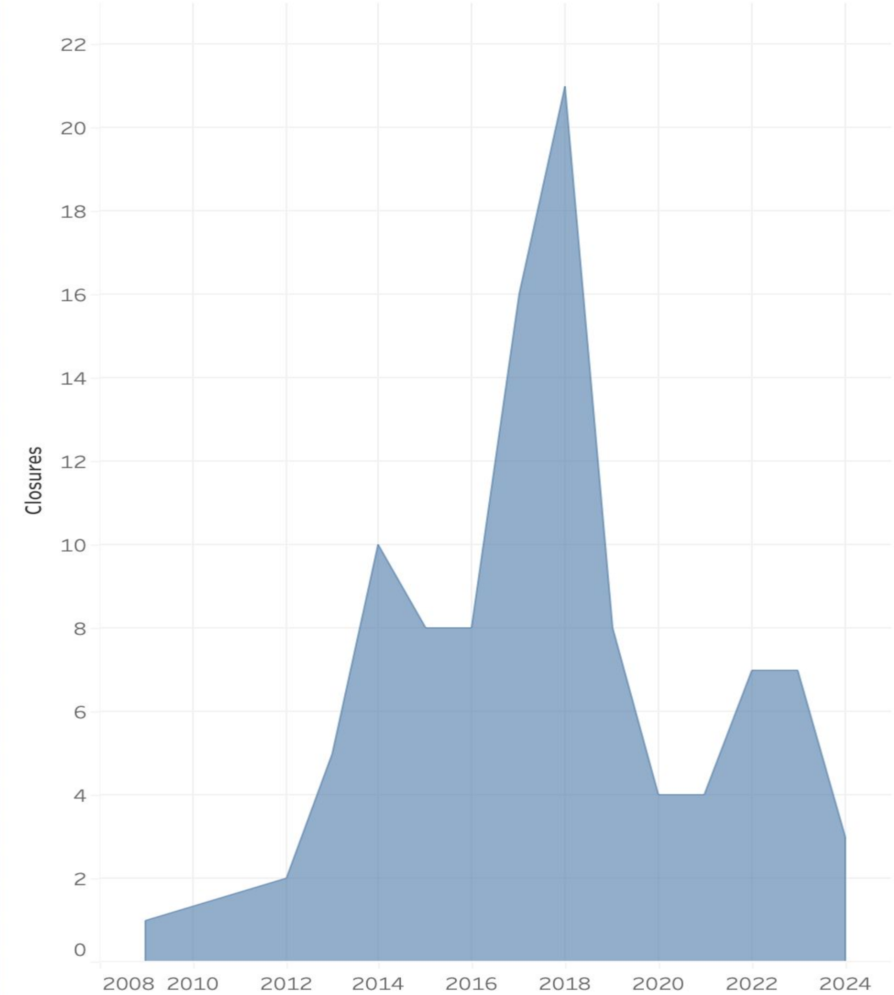
03

THIRD PARTY FACTORS

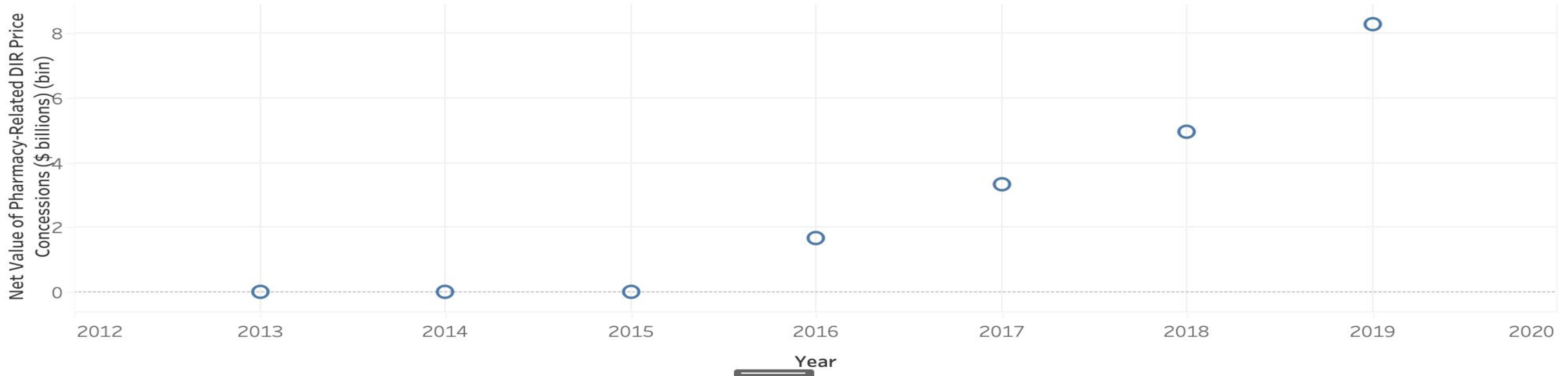
Area charts of total availability rate and rent prices



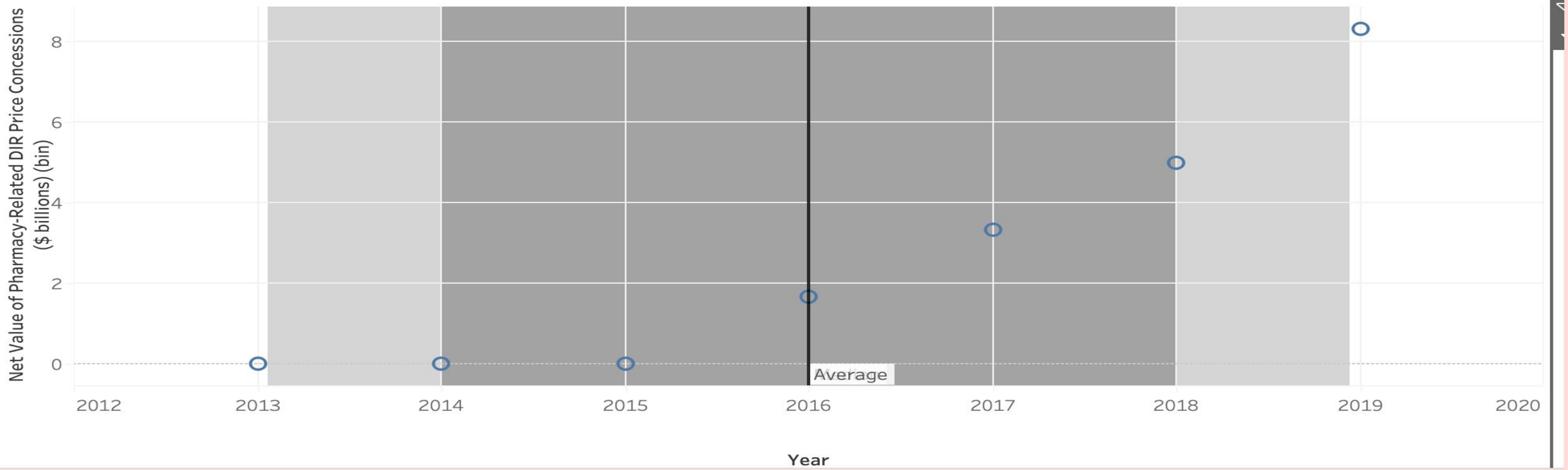
Area chart of Pharmacy closures

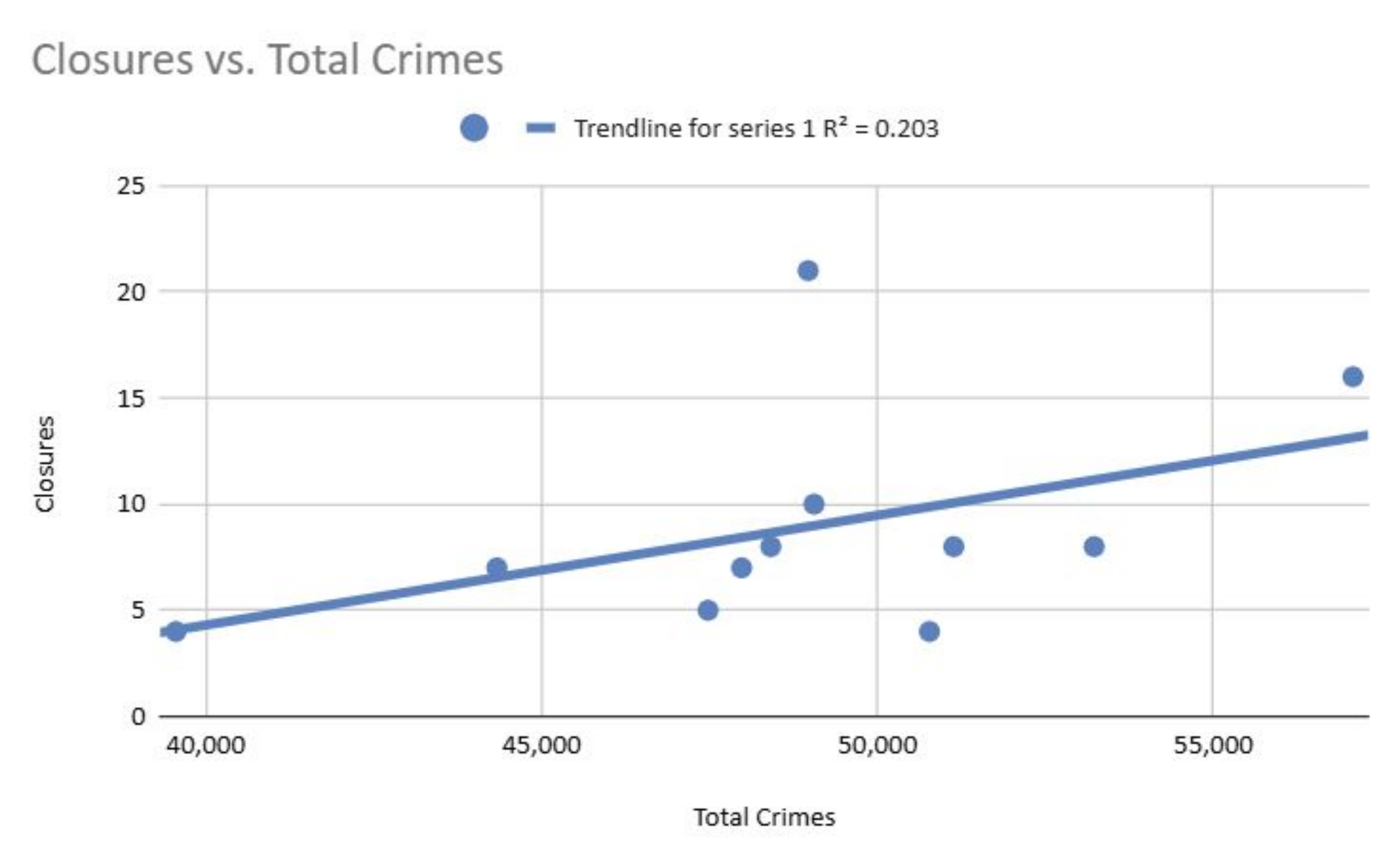


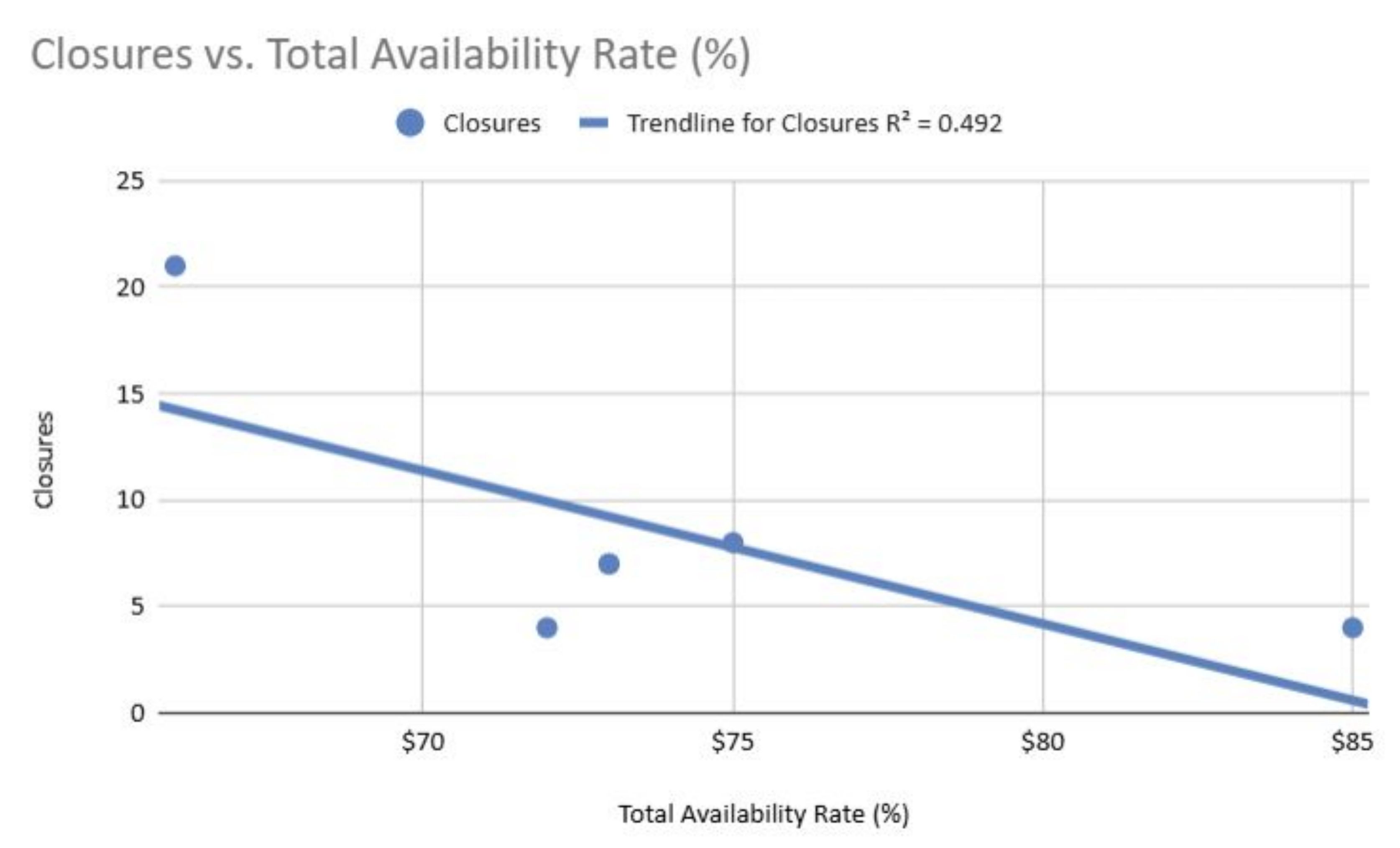
Scatterplot for net value of pharmacy-related DIR Price concessions



Scatterplot with average for net value of pharmacy -related DIR Price concessions



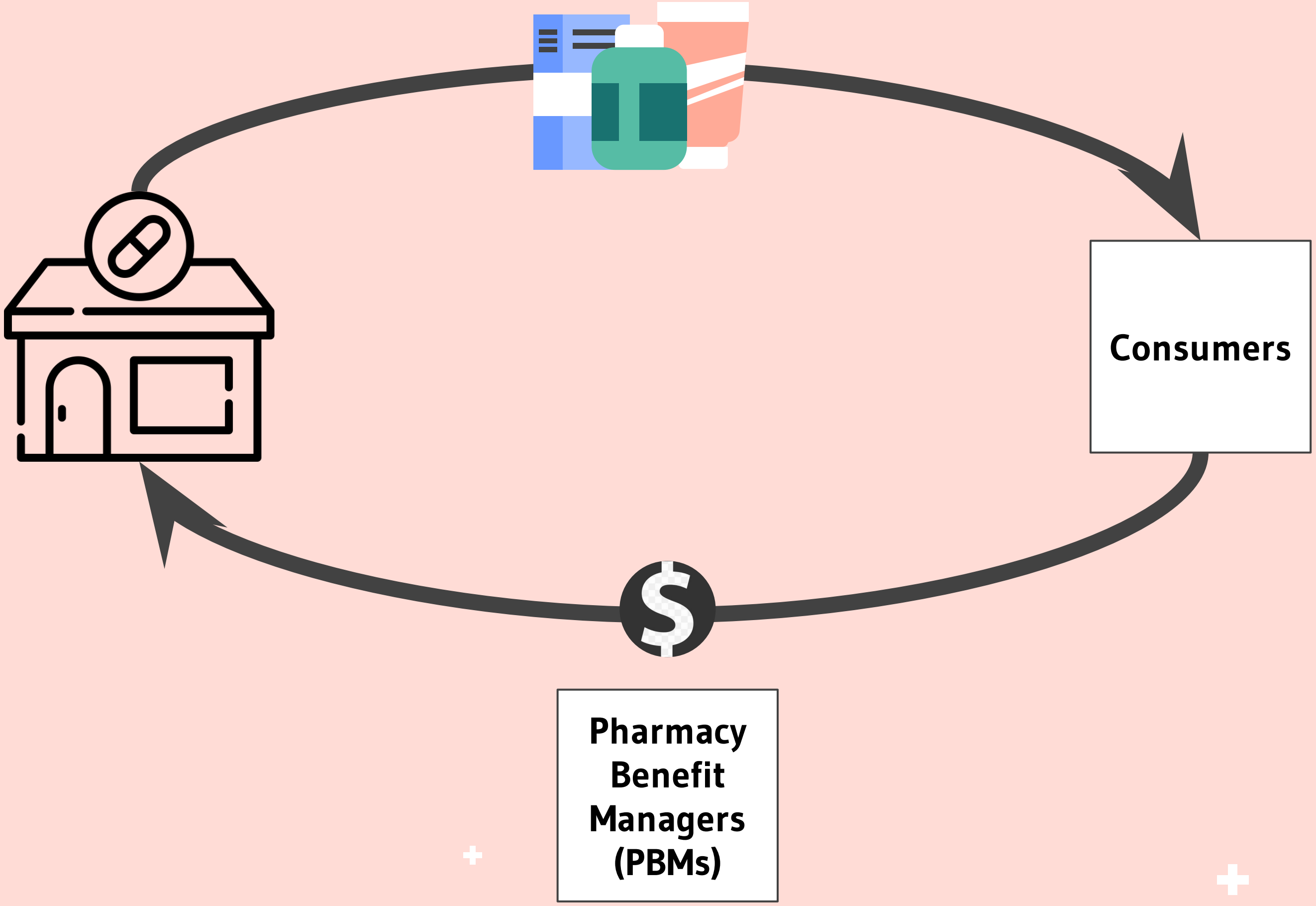

Closures vs. Total Crimes
Trendline for series 1 R² = 0.203
25
20
15
10
5
0
Closures
40,000
45,000
50,000
55,000
Total Crimes

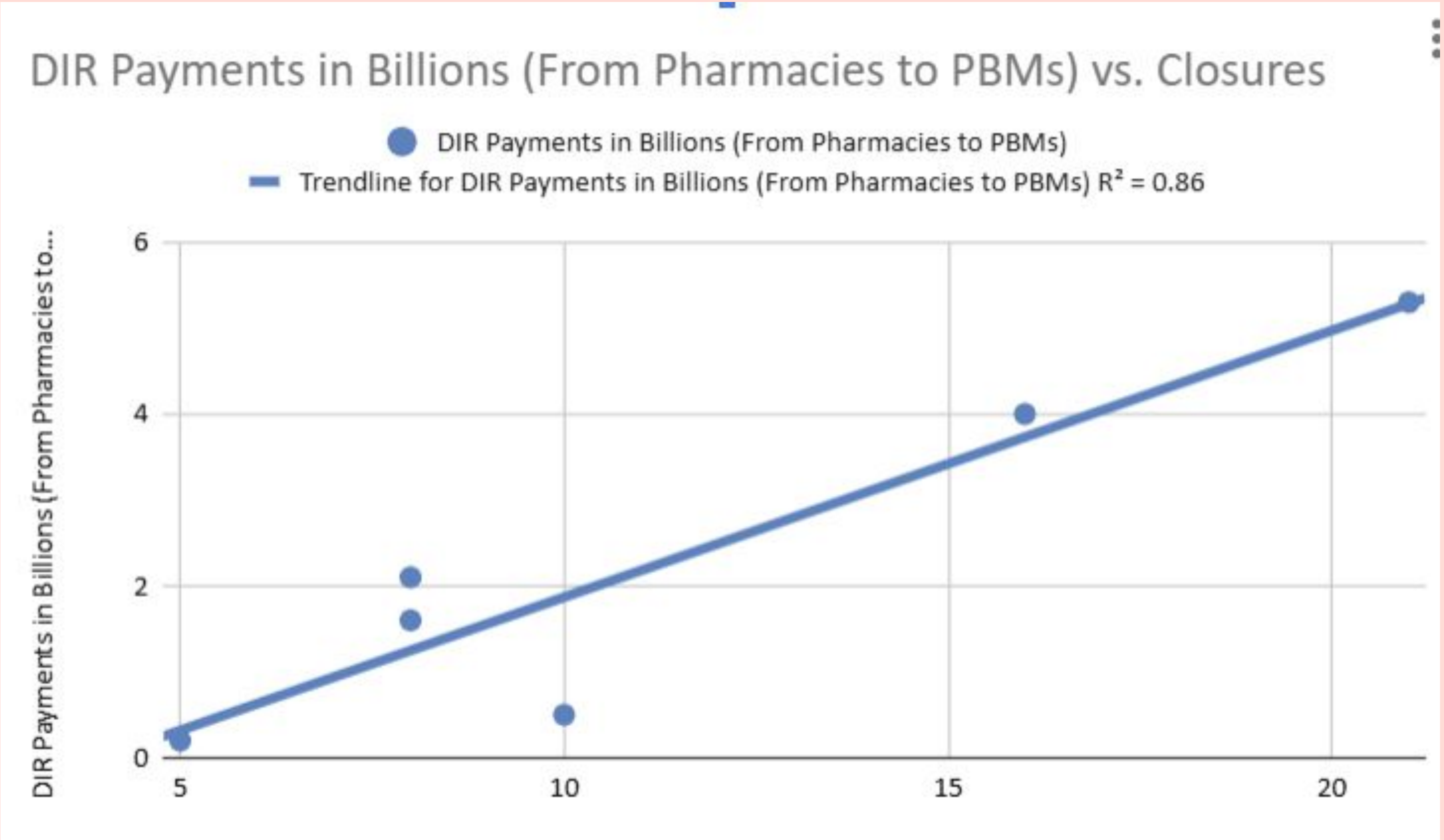

Closures vs. Total Availability Rate (%)
Closures
Trendline for Closures R^2 = 0.492
25
20
15
10
5
0
Closures
$70
$75
$80
$85
Total Availability Rate (%)

ONE LAST FACTOR: PBMs

Year	Closures	Total Crimes	Total Availability Rate (%)
2013	5	55,562	$66
2014	10	55,248	$75
2015	8	60,202	$85
2016	8	54,721	$72
2017	16	63,508	$73
2018	21	59,382	$73
2019	8	57,253	$75

Chain of Distribution




DIR Payments in Billions (From Pharmacies to PBMs) vs. Closures
DIR Payments in Billions (From Pharmacies to PBMs)
Trendline for DIR Payments in Billions (From Pharmacies to PBMs) R² = 0.86
DIR Payments in Billions (From Pharmacies to...
6
4
2
0
5
10
15
20

Celebrity Faces

Princy Ramani, Teia Hapani, Jason Avina

Goal

To build some AI programs that accept celebrity face pictures as input and output a prediction as to which celebrity it is.

Input: celeb faces

Output: label prediction

We compared four models: a baseline ANN, a custom CNN, VGG16 using transfer learning, and most recently, ResNet50 with aggressive augmentation and class weighting to balance underrepresented celebrities.

Files In Project

`preprocess_save.py`
Preprocesses and saves images + labels as NumPy arrays (`X_all.npy`, `y_all.npy`).

`ANNtrain.py`
Trains a basic Artificial Neural Network on flattened images.

`clbCnn.py`
Trains a Convolutional Neural Network (CNN) for face classification.

`clbVgg16.py`
Uses transfer learning with VGG16 and fine-tunes the last 4 layers.

`resnet50.py`
Uses pretrained ResNet 50 + class weights + advanced augmentation.

`celebrity_face_classification.py`
Full training and prediction pipeline in Colab (combines ANN, CNN, VGG16); good for demos.

preprocess_save.py

The model is preprocessed using OpenCV (cv2), which is a powerful library for processing images and videos. It converts images into NumPy arrays, making them machine-readable. NumPy is a high-dimensional array system that stores image data in formats like RGB, which the computer can efficiently process.

We use train_test_split to divide the dataset into training and testing sets, helping evaluate the model's performance. The Label Encoder is used to convert categorical labels (like class names) into numerical values since machine learning models operate only on numbers. this is a nice program because it saves the output as a file, so easier to rerun

🧠 ANN Model – Baseline Classifier for Celebrity Faces

Input: 224×224 RGB images, flattened

Architecture: Flatten → Dense(300, relu) → Dense(100, relu) → Dense(#classes, softmax)

Training: 20 epochs | Optimizer: Adam | Loss: Sparse Categorical Crossentropy

Data: Preprocessed .npy files (X_all.npy, y_all.npy)

Accuracy: 🏋️ Train: 23.19% | 🧪 Test: 13.89%

Overall Purpose: Benchmark for comparing against CNN & transfer learning model. Kind of like trying to memorize a jigsaw puzzle piece by piece, pixel by pixel, not by understanding how the pixels or pieces fit together. Its not coming up with filters for the images. Works for low dimensional, structure data, but struggles with complex images.

🧠 CNN Model – Custom Convolutional Neural Net

Input: 224×224 RGB images

Architecture: Conv2D(32) → MaxPool → Conv2D(64) → MaxPool → Flatten → Dense(150, relu) → Dense(17, softmax)

Training: 10 epochs | Optimizer: Adam | Loss: Sparse Categorical Crossentropy

Data: Preprocessed .npy files (X_all.npy, y_all.npy)

Accuracy: 🏋️ Train: 100% | 🧪 Test: 25.56%

Overall Purpose: Like learning to recognize jigsaw puzzle pieces by identifying patterns: edges, colors, corners, shapes — not individual places for each. CNNs use filters that scan across the image to capture spatial structure and reuse weights, making them much more efficient and accurate than ANNs for images.

🧠 VGG16 Model – Transfer Learning

Input: 224×224 RGB images

Architecture: VGG16 (frozen layers) → Flatten → Dense(400→500→256 relu) → Dense(17, softmax)

Training: 5 epochs + early stopping | Optimizer: Adam (lr=0.0001) | Data Augmentation

Data: .npy files + ImageDataGenerator (rotation, zoom, shift, flip)

Accuracy: 🏋️ Train: 82.99% | 🧪 Test: 53.47%

Overall Purpose: Uses pre trained ImageNet features to improve accuracy on small dataset. Like someone who has solved thousands of similar puzzles before — they start with an advantage. VGG16 brings pretrained puzzle-solving strategies, then adapts them to your specific puzzle.

🧠 ResNet50 Model – Advanced Transfer Learning

Input: 224×224 RGB images

Architecture: ResNet50 (frozen base) → GlobalAvgPool → Dense(256, relu) → Dropout → Dense(17, softmax)

Training: 5 epochs + early stopping | Stratified 80/20 split | Optimizer: Adam (1e-5) | Loss: Sparse Categorical Cross Entropy

Augmentation: Heavy (rotation, zoom, shift, shear, flip) + Class Weight Boosting

Accuracy: 🏋️ Train: 33.61% | 🧪 Test: 39.72%

Purpose: ResNet is like a master puzzle solver who uses a notepad to remember what they've already assembled, and draw shortcuts to avoid redoing the same sections. Unlike a traditional CNN or VGG16, which build layer by layer in a straight stack, ResNet uses residual connections — allowing the model to skip layers and pass information directly across the network. This would have worked better with more epochs for sure.

Results

For our images vgg was the best, but resnet with more time and epochs and hyperparameter adjustment had the capability to improve and outperform, possibly. ANN and CNN were tried exhaustively and had a much harder time, due to their lower complexity and inability to handle complex images as easily.

Also Princy and Tiea built a hugging face app:
https://tiea-celebrity-face-app.hf.space/?__theme=system&deep_link=0-dicxMK4vQ

Thank You!