**Slide 1: Title Slide**  
Hi everyone, my name is Jannet Castaneda Sanchez, and today I’ll be presenting my STAT 418 final project: the FDA Drug Recall Classifier. The FDA currently oversees recall strategies, assesses recall effectiveness, classifies recall severity, and broadcasts recalls. The recalls can either be voluntary by the manufacturer or mandated by the FDA.

The recall classification provides a general understanding of the nature and urgency of the recall. The FDA classifies the recall into one of three categories either Class 1, Class 2, or Class 3 based on how risky the product is. Class I recalls are the most dangerous, often involving the risk of serious injury or death. Class 2 is given to products determined to have caused temporary or reversible health problems or have a slight chance of serious adverse health consequences. The last class (class 3) label is used for products that are unlikely to cause harm, but violate FDA regulations. This project predicts the severity of a drug recall based on the reason provided in official recall notices.

**Slide 2: Problem & Motivation**  
Let’s start with the problem. Drug Recall process isn't always immediate. Sometimes it takes time for investigators to review and label these notices, which can delay action.

My goal was to create a tool that can automatically predict recall severity based on the "reason for recall" text. The motivation is simple—if we can help regulators, researchers, or even the public identify high-risk recalls earlier, we can potentially reduce harm and act faster.

**Slide 3: Data Collection & EDA**  
I collected data from the FDA Enforcement Report API. The dataset contains about 15,000 drug recall events from 2012 to 2024. I focused on the reason\_for\_recall, which is a short text field that explains why the drug was recalled. Other variables included classification, firm, and product\_description.

In my exploratory data analysis, I found that Class II recalls are the most common—about 60%—followed by Class III and then Class I. I used Term Frequency-Inverse Document Frequency to extract the most informative terms across classes, and word clouds helped visualize patterns in the language. For instance, Class I recalls frequently mentioned terms like "life-threatening" or "contamination."

**Slide 4: Model & Architecture**  
For the model, I used logistic regression with TF-IDF features to predict the classification. After balancing the classes through stratified sampling, I achieved an accuracy of about 81%, which I considered reasonable for a baseline model.

On the deployment side, I used Plumber in R to build an API, which I hosted on an Amazon EC2 instance. Then, I created a Shiny web application hosted on shinyapps.io. The app allows users to input a recall reason and receive a predicted classification in real time.

You can think of this project as an end-to-end pipeline—from raw text data, to prediction, to deployment on the web.

**Slide 5: Takeaways & Next Steps**  
Here are a few takeaways. First, Natural Language Processing methods like Term Frequency-Inverse Document Frequency, and logistic regression can meaningfully assist in classifying high-risk recalls. Second, deploying the model and app required working across multiple tools—APIs, cloud hosting, Shiny apps, and Docker.

For next steps, I’d like to add batch input support, so people can paste in multiple recall reasons at once.

If you’d like to explore the full project, the GitHub repo is public and includes the API code, Shiny app, and documentation.

**Closing**  
Thanks for listening. I’d be happy to answer any questions or demo the app!

Let me know if you'd like me to help you rehearse or edit this for a recorded video.

EC-Terminal

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