Bot || !

Team #2

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Project Synopsis

Bot || *!* leverages existing and user-generated data to classify pathogenic social media accounts. Its applications include identification and removal of spam accounts that influence public opinion.

Project Description

In recent years, pathogenic accounts have been used as a tool for influencing the perception of the public. For instance, such accounts significantly impact the news people see every day, skew perceptions on important global events, sow discord into populations, and ultimately undermine the effectiveness of the democratic processes. The ebb and flow of the battle against pathogenic social media has blossomed into a vibrant field. *Bot* || *!* seeks to aid in the fight against the far-reaching negative impacts of pathogenic social media by employing an innovative approach to the classification of pathogenic accounts.

Humans have the uncanny ability to solve incredibly complex problems quickly. Uber tapped into this innate ability to classify signs for their self-driving car technology. Likewise, we will use the power of human perception to classify pathogenic social media accounts, effectively crowdsourcing the training of a pathogenic account classifier. It is possible this novel approach will lead to a substantial contribution to the field. Once our classification system is sufficiently accurate, tech companies and intelligence agencies alike can utilize the data *Bot* || *!* produces to further their investigations.

The complexity of the project affords us the opportunity to develop our skills across the tech stack. We will integrate a sublime user-experience, robust data storage systems, and a novel analytics engine to support the training of our classifier. By March, we will have a mobile and web application where users can the authenticity of an account. Their decision will work its way into our analytics engine to produce an effective data stream for our classifier. This process will iteratively tune the classifier until it can confidently judge the authenticity of a social media account. The data we select for analysis will combine existing techniques with algorithms developed from our understanding of the psychology behind how people interact with social networks and respond to content. This approach will allow us to extend the capabilities of our algorithms and add features as far as our timeline allows.

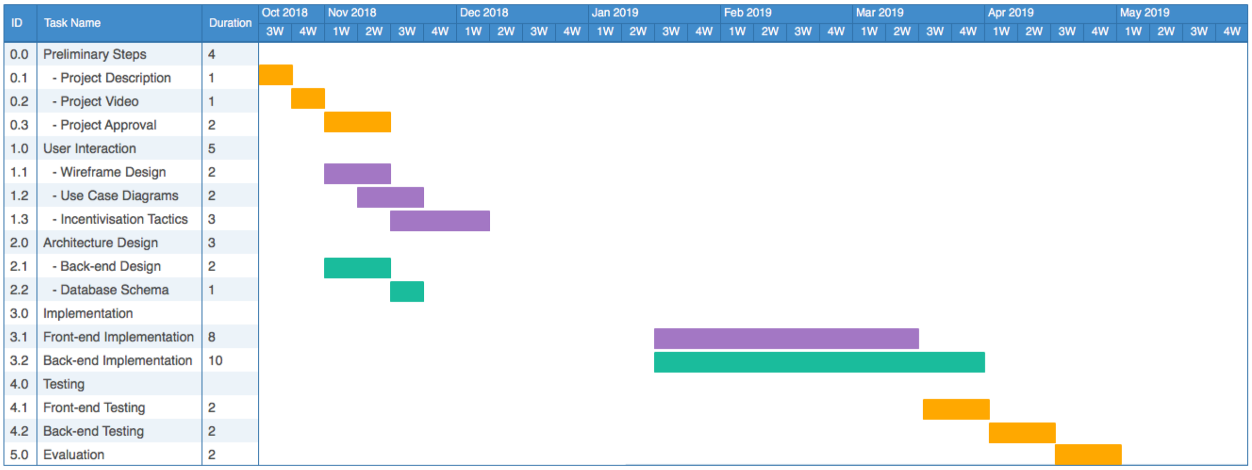
Project Milestones

Milestones are integral to the success of the *Bot || !*. They serve a two-fold purpose to guide our inspiration and hold us to account. After a thoughtful discussion at the beginning of the fall semester, we established a series of milestones to guide our development throughout the year. They consist of two types: design-oriented and implementation milestones.

The former group drove our efforts throughout the fall. In particular, we wanted to accomplish three major things: design an engaging and user-friendly application, establish an extensible backend architecture including database schema and API protocol, identify useful public datasets on which to initially train our ML model, and create a dynamic workflow for the implementation phase. The first is the creation of a comprehensive project timeline. We were successful on all fronts. The wireframe for the application was completed on November 13th by Liam Ormiston. It is modeled after well-known apps like Tinder and details our unique incentivization method. Later in the month of November, after identifying key public datasets and researching Twitter's API, we established the schema, RDBMS service, computing instance, an API protocol for *Bot || !*. Building on the momentum, we established our Github organization and set up repositories for our various subprojects. Ahead of schedule, we used the remainder of the semester to work out kinks in our design like where we would host the database and how we would aggregate data from Twitter. Additionally, Patrick Canny set up a continuous integration pipeline using Travis to improve our future workflow.

Beginning in January, we set our eyes on the implementation of our endeavor. Our goals for this semester revolve around generating a respectable minimally-viable product and refining our machine learning implementation. At the beginning of February, we will have all infrastructure (e.g. database, cloud-computing instance, servers, etc.) up and running as well as all necessary permissions (i.e. Twitter API keys) acquired. At the end of February, we will have a fully functional data aggregator shoveling fresh tweets and profiles into our database and a front-end application that acquires data from user opinions to augment our internal dataset. By the end of March, we will have a simple machine learning process to train. As the semester winds down in April, we will have fully tested our system to ensure performance. Finally, in early March, we will open the application to the public with the intent of stress testing both our project and the precision of our initial hypothesis.

Gantt Chart



Project Budget

Item	Price	Quantity	Timeline	Description	Purpose
Sketch	$99	1	Upon Approval	Digital Design Software	Enables us to create a template for our UI
Google Play Store	$25	1	Near completion	Publishing permission to the Google Play Store	Publishing
Apple Store	$99	1	Near completion	Publishing permission to the Apple Play	Publishing
Hosting (Digitalocean)	$10/mo	5	Ongoing	Hosting for our api and database. Eventual hosting for ML	Allows us to make sure our API and processes will be running 24/7
Total	$273				

Work Plan/ Roles

Liam - Application developer, front-end engineering
Damian - Deployment/build engineer, data visualization, internal API developer
Lane - Backend engineering, internal API developer, data engineering
Patrick - Data engineering, data modeling, application development
Taylor - Backend engineering, data modeling, utility developer

Preliminary Project Design

"Bot || !" has five main components. They are the frontend, API, data storage, analytics, and data aggregation. Each piece functions independently yet contributes to the overall mission in significant ways. In a nutshell, data comes into the system from users via the frontend and from social media services on the backend. The flow of accounts from front to back via the API continually refines our classifier. The classifier then produces conclusive data regarding our data lake on a frequent basis for the use of interested parties.

More precisely, here is a walk-through of the life of datum in our architecture. We store pre-existing data in a MySQL database that we will use for our mobile application. This data consists of twitter accounts that have been categorized as pathogenic, non-pathogenic, and indeterminate. We collect said data by way of our Data aggregator (see **Figure 1**.) and pre-existing datasets.

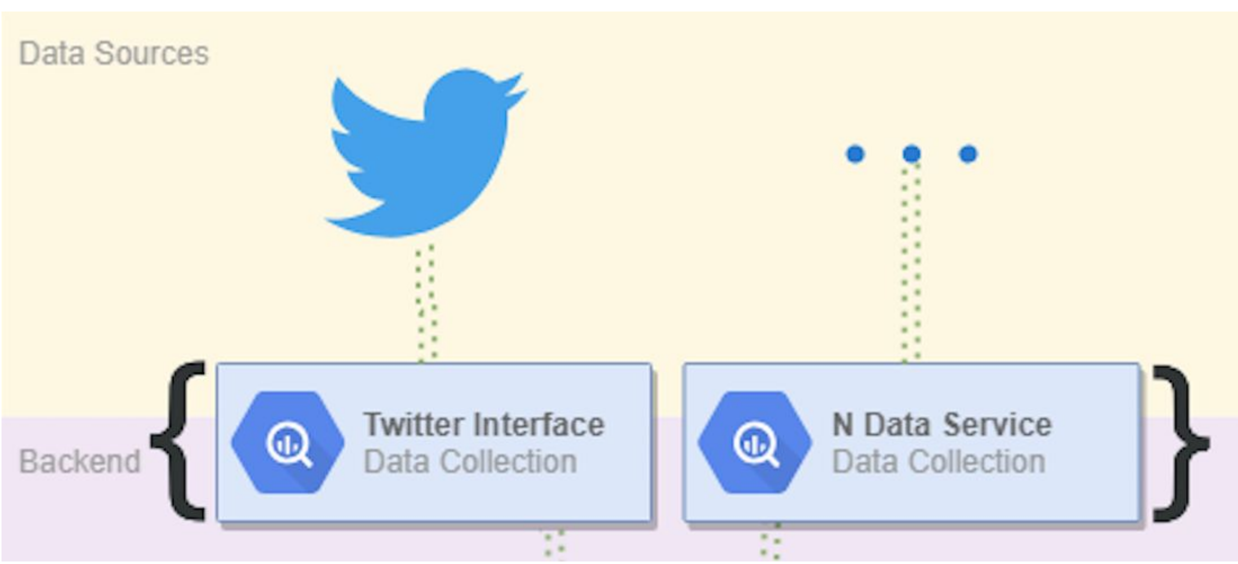


Figure 1

The application takes that data and presents an account to a user as shown in **Figure 2**.

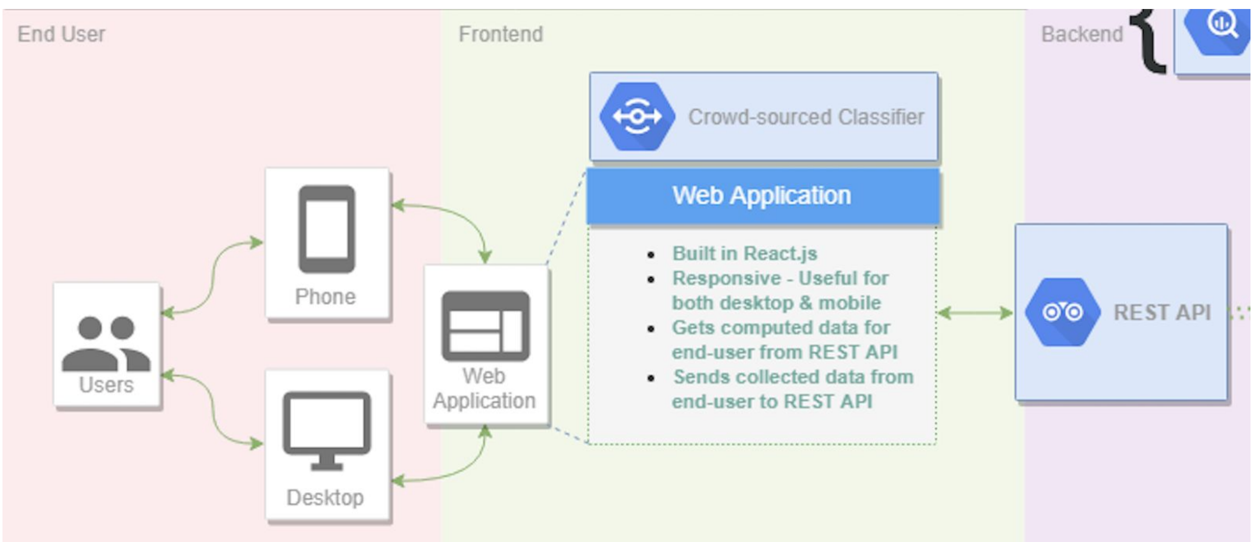


Figure 2

The user then identifies the account as either pathogenic or non-pathogenic. The user's response is then sent back to the cluster and stored in a separate dataset with the identified field. This process can be seen in **Figure 3**.

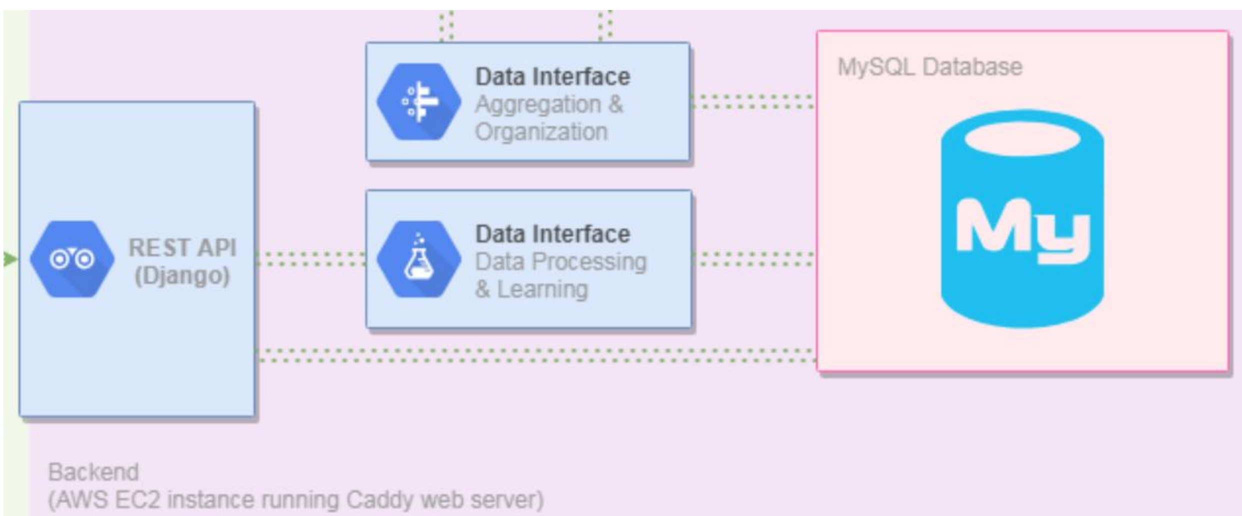


Figure 3

From there, we reconcile this modification to the dataset to generate the classifier.

The frontend application is built on top of a web-based language that can be ported to mobile environments. ReactJS and React Native are the technologies underpinning the frontend. ReactJS is a Facebook language designed to quickly and easily create components that "react" with different environments the application may exist within. It perfectly fits our use case by allowing us to create a single application for web, Android, and IOS. React Native then takes the React code and converts it into native code for each mobile platform.

The application is made up of four different views. The first view the user sees is an account creation/login screen. The user can either log in or create a new account if they do not already have an account. The users are then taken to the main view where they see a username, profile picture, bio, and the last five tweets associated with that account. The user then swipes left or right to classify the account as pathogenic or not, respectively. When the user swipes to make their decision, they are then presented with another account's information that will continue the classification process. The newly classified account is then sent to the backend to be analyzed and categorized. The third view is the leaderboard. It shows how the user stacks up to other users on the app. For each correct classification, where an account has already been identified, a user will receive +1 point. If they incorrectly classify an account, they will receive -1 point. For every classification that was unidentified previously but two users come to the same identification, both users receive +5 points. The final view is a profile where the user can see and edit their account information.

If our application is to have any notable impact, we must develop an effective framework for aggregating data from a variety of sources. As displayed in **Figure 1**, we primarily mine account data from Twitter. To do so, we concurrently utilize a set of API keys to maximize our data-mining efficiency. We use the Python learning library (described below) to ensure the usefulness of the accounts we mine. This aggregation layer is also where we will investigate the merit of bringing in data from other sources, and the entry point for all data to be consumed by our system. This involves setting up a data aggregator that listens for data at the sources we specify and then sends that data to the database. This is advantageous since it is easily extensible to any set of sources that we may find valuable in the course of our work.

One of the crucial pieces of our application will be the data processing and analytics layer. In this piece of the application, we use machine learning algorithms alongside data science models of our design to derive new meaning from our dataset. The primary means of evaluating and manipulating this large dataset is a custom Python library that solely runs machine learning algorithms on the training data and to serve the results reasonably. When compared to other spam account classifiers, one distinguishing characteristic of our software is the integration of data collected through user interactions. Though innovative, we must account for increased uncertainty in our system. We clean and process our incoming data to ensure the succinctness of our datasets, and maximize their utility. This process is a feature of the library, along with a set of machine learning models that the data can be passed through for training and testing. Ideally, we will work towards a position where we can update our models each time a new piece of data comes in, resulting in the most current real-time processing. Of course, with Python, speed will be a concern in this layer in particular. In addition to this library, we need to find a good way to visualize and interact with our models. This is where using a tool such as Jupyter Notebook or Tableau comes into play. Finally, this inference layer of our application will need to be able to communicate with both the backend data storage layers, as well as the

REST API. We will store our modified and/or generated datasets in our database in order for our previously processed data to take effect in future iterations. We use the REST API and our data library to intelligently serve up data to the frontend.

Design Constraints

Programming Language:

For our project, we aim to make our app accessible to everyone. Because of this, we need a language that can work on all platforms - web, iOS, and Android. Most companies would have different departments in charge of each platform using native languages for each. However, we are only a small team that cannot dedicate such time and resources to a developer with native languages for each platform. Therefore, we chose to use a web-based language that can adapt to native environments for iOS and Android such as React. Although using a language platform that can be used to build native mobile apps is useful, it will never be the same as developing with the native language. Understanding this constraint, we strive to create an app that does not require a lot of native features. The fewer native features our app requires, the easier it is to program in a non-native programming language.

Data Aggregation:

In order to build an effective classification algorithm, we need social media accounts. The multiplicity of social media platforms at our disposal solves this problem; In return, it presents a set of challenges. We must develop a data aggregation engine that takes input from multiple sources, i.e. Twitter, Facebook, Instagram, etc.; and condenses it into a consistent format and sends the data to our relational database. Our schema must account take into consideration the multitude of information at our disposal. Therefore, we must design it with the utmost care.

Real-time Needs:

Because “Bot || !” interfaces with real end users, latency is vital. Our relational database provides us with the ability to easily interface with our front-end application, data-aggregator, and machine learning process. However, balancing the demands of all three systems while seamlessly providing service to our users requires the implementation of algorithms that efficiently move, update, and translate data.

Ethical and Intellectual Property Issues

Given the gravity of our subject, we must consider a myriad of ethical and intellectual property concerns. Fortunately, our project trods well-marked territory, so similar projects have been done previously. Though helpful, it presents a new set of challenges. We must be mindful of our progress and ensure that we are not infringing on the intellectual property of others in the pursuit of innovation.

Since our project partially deals with gathering user data, we will need to implement terms of use between ourselves and users. This is to promise to our users that we will not utilize their personal data outside of account lookup. On our end, this also means that a secure way to store user information without actually being able to access that information will need to be utilized. This could be down through some form of hashing, or through utilizing some pre-existing tool. Similar project designs to our proposed project exist, so a key ethical concern for our team will be ensuring that our project is unique and distinguishable from the currently existing projects. This will be primarily addressed through implementing a hybrid approach between traditional data collection and crowd-sourced data collection and uniquely leveraging both of these sources appropriately. Some of the key contributors we will need to be mindful of are the folks over at the University of Indiana. These people have been doing some development in the area of classifying pathogenic social media accounts, and a lot of their applications are in the same realm as ours. We will want to be good stewards of the profession and ensure that the work we will be doing will not be conflicting with their previous work. We will also seek opportunities to reach out to them if we end up in a situation where it seems that our two concepts seem to be more closely related. Our project also deals closely with how spam accounts impact public opinion, so it will be important that we are not serving up accounts that may be closely tied to hate speech or any derogatory content towards users. We will need to closely curate the accounts we push out to users in order to ensure that the accounts being served are ethically sound.

Preserving our personal IP while also seeking to make a contribution to the field is something that must be kept in mind as we move forward into creating our project. We would like to be able to make a small mark on the field of data science in some way, either by contributing new datasets, algorithms, or a mixture of both. Since we seek to share our findings, we will likely be publishing our work to a public GitHub repository and sharing any information we find with a subset of the data science community. In our initial terms of use and agreement, we will need to add clauses designating how our software may be used and further distributed. A good place to start with this is licensing our project under a public license such as the MIT license. We will also identify potential places where we may be infringing on others' IP, and do what we can to ensure that we are using all forms of software and/or datasets ethically. Some potential places where these concerns need apply are any use of an ML platform, HDFS distribution information, use of public or private datasets and the like. We will also need to ensure that any non-original code that we choose to use is well documented and cited in our work.

Change Log

- Hadoop cluster removed from the budget
  - We no longer need a Hadoop cluster to accomplish our goals.
- Refined milestones within the "Project Milestones"
  - Dates-of-completion needed to be added to first semester goals. Second-semester goals were a touch vague, so now they reflect our implementation goals.
- Removed HDFS cluster where mentioned
  - We no longer need a Hadoop cluster to accomplish our goals.
- Elaborated on MySQL usage where mentioned
  - We will rely more heavily on this database now that we are no longer using a Hadoop cluster.
- Updated **Figure 3** to reflect new backend architecture
  - The old figure depicted our usage of a Hadoop cluster. The new figure highlights the importance of MySQL in our architecture.
- Added hosting to the budget
  - In the original proposal, we considered going through KUIT. However, managing our own resources better aligns with our project goals and desired learning outcomes.
- Made tense usage consistent throughout the document
  - Inconsistencies and an over-reliance on the past-perfect and future-perfect tenses made the document read poorly.
- Reworded sentences for brevity and clarity throughout the document
  - Again, these changes improve readability.

References

"Early Identification of Pathogenic Social Media Accounts" (Alvari, Shaabani, Shakarian)
"Uncovering Large Groups of Active Malicious Accounts in Online Social Networks" (Cao, Yang, Yu, Palow)
"Maximizing the Spread of Influence through a Social Network" (Kempe, Kleinberg, Tardos)
"A Randomised Controlled Trial of Social Network Targeting to Maximize Population Behaviour Change" (Kim, Hwong, Stafford, et. al.)
"Detecting Influence Campaigns in Social Networks Using the Ising Model" (des Mesnards, Zaman)
"The Rise of Social Bots" (Ferrara, Varol, Davis, Menczer, Flammini)