# WITTOO

## Machine Learning Driven Social Engineering

Charles Herring Co-Founder, CTO

me@CharlesHerring.com https://CharlesHerring.com @charlesherring

# **About Charles**



**1995-2002**: Forward Deployed US Navy Hornet Avionics Tech

2002-2005 US Naval Postgraduate School Network Security Group Division Officer sk3wl Of rOOt team member





# **InfoWorld**

2003-2008: InfoWorld Test Center Contributing Product Reviewer – Network and Information Security

2005-2012 DoD Security, Data & Workflow Consultant

2012-2016: Consulting Security Architect for Lancope then Cisco Systems

**2016** CTO & co-founder at WitFoo







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CISCO

## Disclaimer

Information in this presentation is intended to protect against illegal or harmful social engineering and human manipulation or to be used in benevolent endeavors.

## Please do good and obey the law.







# **Old School Social Engineering**

- Based on "Confidence Games" (Cons)
- Target a "mark" to achieve inappropriate action
- Requires understanding of "mark" (agent)
- Manipulates existing human vulnerability







# Second Generation Social Engineering

- Bulk, mass attacks
- Phishing
- Robocalls





# Social Engineering with ML

- Need the Cohort (not a specific agent) to take action
- Long term training will transform agent values (create vulnerability)

They talk of a man betraying his country, his friends, his sweetheart. There must be a moral bond first. All a man can betray is his conscience.

Joseph Conrad



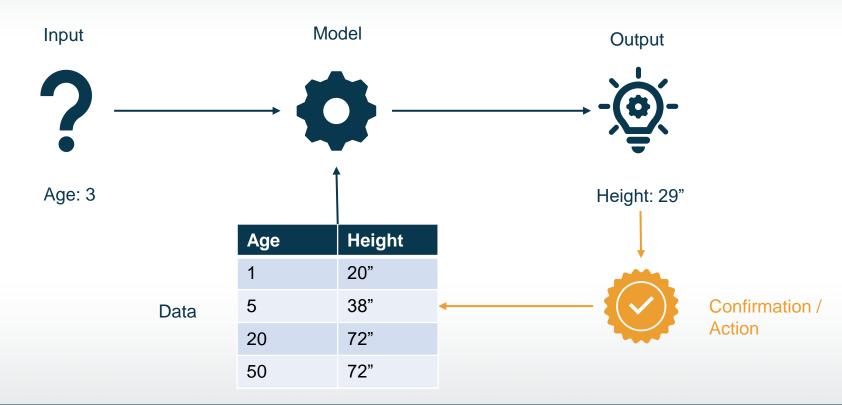
# **Relentless Manipulation**

 "We've created a world in which online connection has become primary. Especially for younger generations. And yet, in that world, anytime two people connect, the only way it's financed is through a sneaky third person who's paying to manipulate those two people. So, we've created an entire global generation of people who were raised within a context with the very meaning of communication, the very meaning of culture, is manipulation." – Jaron Lainer in The Social Dilemma



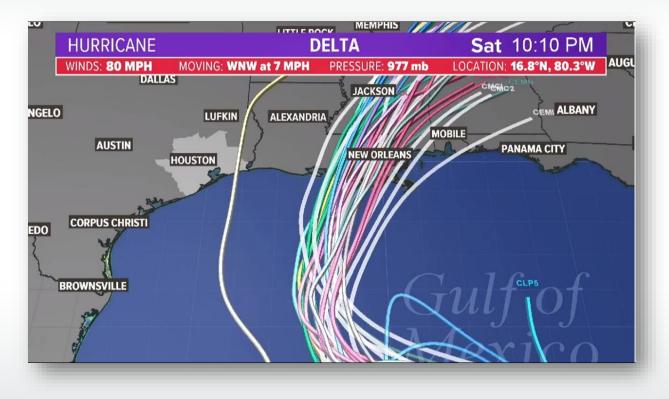
# Machine Learning Basics

# **Supervised Learning**





## **Data and Models**





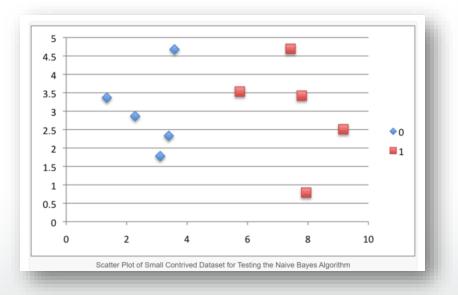
# **Common Models**

- Naive Bayes
- Nearest Neighbor
- Decision Trees
- Linear Regression
- Support Vector Machines (SVM)
- Neural Networks

https://towardsdatascience.com/types-of-machine-learning-algorithms-you-should-know-953a08248861

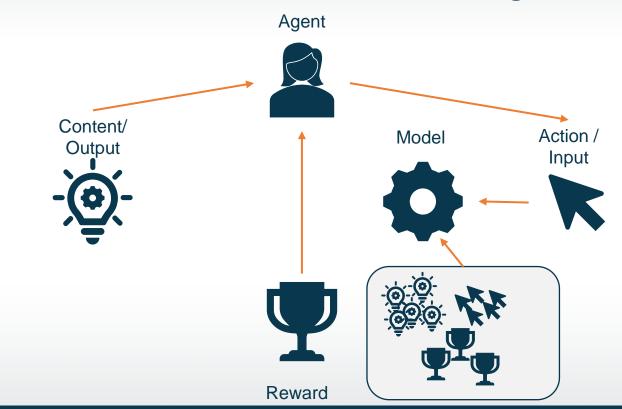
# Naïve Bayesian Python

 https://machinelearningmastery.com/naive-bayes-classifierscratch-python/
# Example of separating data by class value



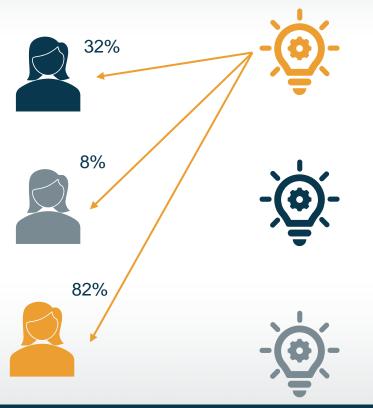
1	# Example of separating data by class value
2	
3	# Split the dataset by class values, returns a dictionary
4	<pre>def separate_by_class(dataset):</pre>
5	separated = dict()
6	<pre>for i in range(len(dataset)):</pre>
7	vector = dataset[i]
8	class_value = vector[-1]
9	if (class_value not in separated):
10	<pre>separated[class_value] = list()</pre>
11	separated[class_value].append(vector)
12	return separated
13	
	# Test separating data by class
15	
16	
17	
18	
19	
20	
21	
22	
23	
24	L
25	
	for label in separated:
27	
28	
29	print(row)

# **Reinforcement Learning**





# A/B Testing of Output / Signal / Content





# **Types of Content**

- Text Ad
- Video Ad
- Promoted Pages
- Email
- Snail Mail
- Images

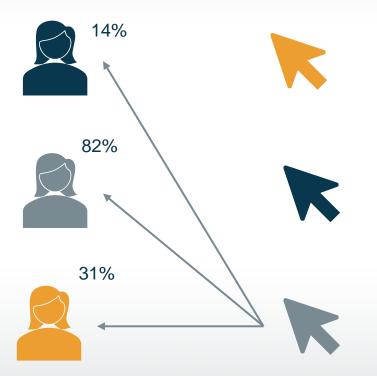


# **Message Considerations**

- Alignment with Values
- Suspicion Triggers
- Language & Dialect Use
- Use of Nostalgia
- Trauma Triggers (Crossing a line)
- Bias Reinforcement
- Trusted Corroboration
- Social Corroboration
- Pain vs. Reward



# A/B Testing of Action



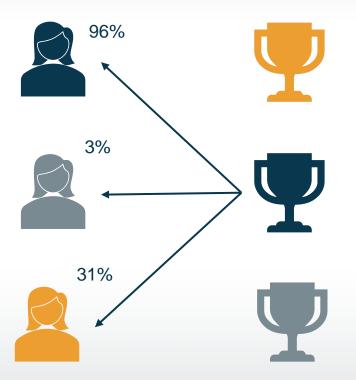


# **Types of Actions**

- Click to Page
- Watch Video
- Play Game
- Fill out Form
- Join a Group
- Install an Application
- Comment / Engage



# A/B Testing of Reward





# **Types of Reward**

- Public Praise like, retweet, comment
- Artificial Prize badge, points
- Physical Prize cash, gift card, prize, beer, meal
- Education Credit CEU, certification
- Celebrity Interaction virtual or physical
- Promise of job
- Romantic Relationship or Encounter
- Confirmation Reinforcement





# **Common Cohort Dimensions**

- Gender
- Age
- Ethnicity
- Religious Belief
- Income
- Location
- Family Status
- Job Type

- Employer Type
- Education Level
- Affiliations
- Relationships
- Entertainment
- Credit Rating
- Net Worth
- Political Association

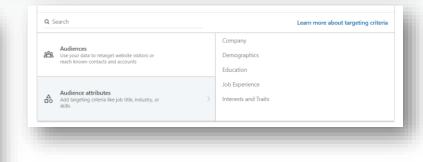
## **Facebook Audiences**

e invaetore	
Create Audience	
Locations	
United States	
Vnited States	Ţ
Q Search Locations	
Detailed Targeting Include people who match <b>1</b>	
Behaviors > Politics (US)	
Likely engagement with US political content (conservative)	
Demographics > Education > Education Level	
College grad	
Interests > Additional Interests	
Grand Rapids, Michigan	
The Hacking Universe	
Interests > Entertainment > Music	
Add demographics. interests or behaviors	Suadestions Browse
Your audience selection is fairly broad.	
Specific Broad Potential Audience Size: 140,000,000 peop	le ()
	Cancel Save

Income		
Household income: top 10% of ZIP codes (US)	$\Box \leq$	
Household income: top 10%-25% of ZIP codes (US)		
Household income: top 25%-50% of ZIP codes (US)		
Household income: top 5% of ZIP codes (US)		
Work		
Employers	q	
Industries		
Job Titles	ď	
▼ Soccer		
Friends of Soccer fans		
Soccer fans (high content engagement)		
Soccer fans (moderate content engagement)		

## LinkedIn Audience

Who is your target audience?	
Include people who have <b>ANY</b> of the following attributes:	Ø
Member Interests Open Source Software	
AND also have ANY of the following attributes:	D
Job Titles (Current) Software Engineer	
AND also have ANY of the following attributes:	Ø
Company (Current Jobs) Steelcase	
Narrow audience further	
Exclude people by audience attributes and Matched Audiences	
inkedIn tools may not be used to discriminate based on personal characteristics like gender, age, or actual or perceived race/ethnicity. Learn more	



#### Useable on Bing Search

# **Google Audience**

Demographics			
Select your demographic target	ing ⊘		
Gender	Age	Parental status	Household income
Female	18 - 24	Vot a parent	<b>V</b> Top 10%
Male	25 - 34	Parent	11 - 20%
Vnknown ⊘	35 - 44	Vnknown 🕥	21 - 30%
	45 - 54		31 - 40%
	55 - 64		41 - 50%
	65+		Lower 50%
	Unknown ⊘		Unknown ⊘

#### Audiences

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Select audiences to define who should see your ads. You can create new audiences in Audience Manager. ⑦

SEARCH BROWSE		7 selected	CLEAR ALL
Who they are (Detailed demographics)	>	Detailed demographics	
What their interests and habits are (Affinity)	>	Employment > Company Size Very Large Employer (10k+ Employees)	⊗
What they are actively researching or planning (In-market and life events)	>	Employment > Industry Manufacturing Industry	8
		Parental Status > Parents Parents of Preschoolers (4-5 years)	8
How they have interacted with your business (Remarketing and similar audiences)	>	Marital Status Single	8
Your combined audiences (Combined audiences)	>	Homeownership Status Homeowners	8
Your custom audiences (Custom audiences)	>	Education > Highest Level of Educational Attainment Bachelor's Degree	8
		Affinity audiences	

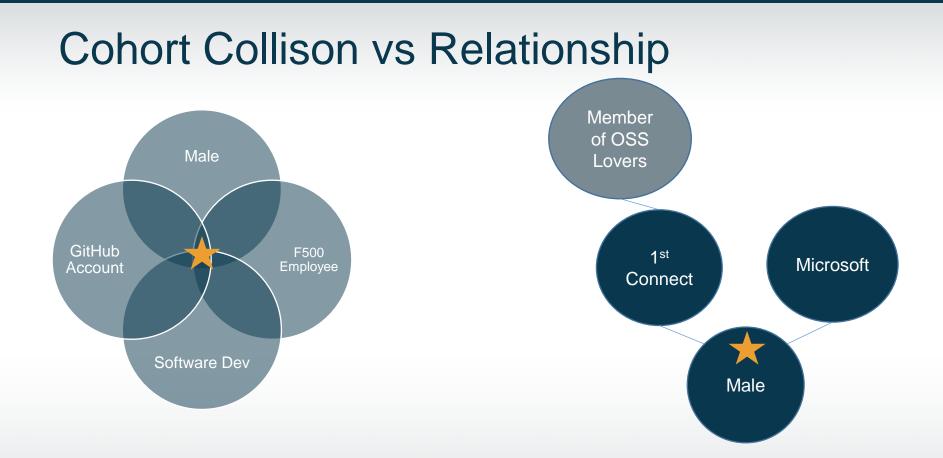
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# **Other Sources of Information**

- Breach Data (Cambridge Analytica, etc)
- Intellius
- Scraping Social Media Sites
- Public Records





# Launching Campaigns

# Humans Move Slowly

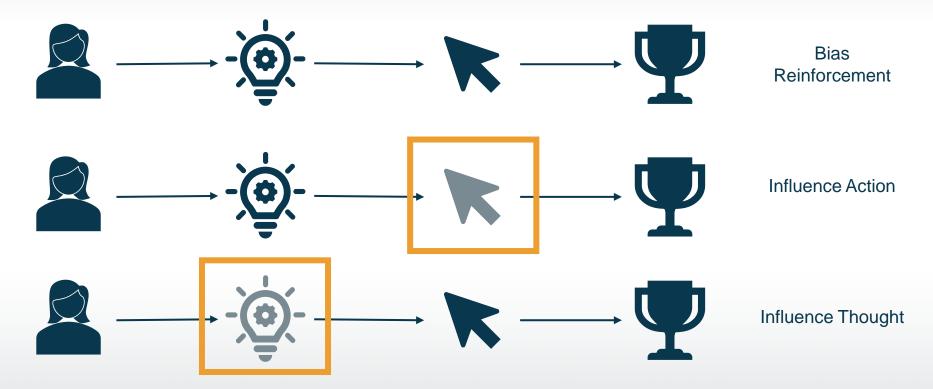
### THE TRADITIONAL SALES FUNNEL



Sales cycles as detailed here can take <u>months or years</u> to complete as agents progress through the process.

Successful progressions will have small, incremental steps requiring the lowest amount of agent change per stage.

# **Agent Transformation**





# **Key Tracking Metrics**

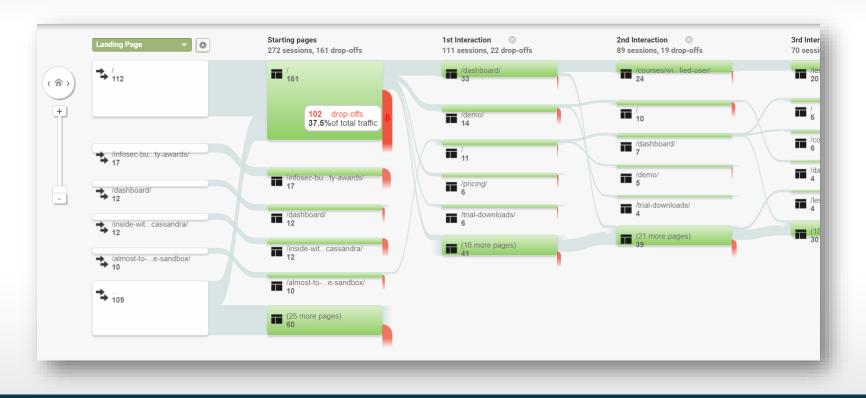
- Agent ID (Preferred) or Cohort ID
- Content ID
- Action ID
- Action State
- Proposed Reward ID

ID	Cohort	CID	AID	AS	RID
1000	1	3	2	0	1
1002	2	3	2	1	1
1000	1	4	2	1	2
1001	2	3	2	1	1

https://test.com/page.php?agent\_id=1001&content\_id=3&action\_id=2&state=fail&reward\_id=4



# **Behavior Flow Analysis**



# **Improving Cohort Definitions**

- What characteristics are shared among funnel exits?
- Are those characteristics missing in continuations?
- Tracking interaction counts to conversion

ID	Age	Politics	Income	Role	Music
1003	57	Near Left	\$120k	РМ	EDM
1198	45	Far Left	\$200k	Exec	EDM
2876	33	Near Right	\$85k	Dev	EDM



# **Multi-stage Cultivation**

**Obtain Followership** 





# Maintaining a Campaign

- Data Mining for Cohort Definition
- Large, diverse, effective content
- Ability to maintain audience (Groups, followers, mail lists, games)
- A/B testing of action delivery
- Reward types
- Decent Model (Naive Bayes)
- Growing Dataset for Model
- Detection Avoidance





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