

KINGMAKER DATA INVESTIGATION

Nov 18th 2024

Created by Michael Segaline, Data Scientist

| On behalf of the volunteers in the Washington State GOP

Bottom Line Up Front: There appears to be definitive evidence of gross-negligence, fraud, and election tampering by Kingmaker Data.

Abstract:

This study was initiated to assess the accuracy of Kingmaker's political sentiment classifications after numerous reports of door-knocking volunteers being placed in dangerous situations due to inaccurate classifications. Using Spokane County voter census data as the benchmark, Kingmaker's classifications—categorized as "strong republican", "likely republican", "strong democrat", and "likely democrat"—were analyzed for alignment with verified voter records. The study hypothesized that Kingmaker's classifications might not be the product of a genuine machine learning model, and its accuracy might be no better than random chance. Leveraging Python, Jupyter Notebook, and statistical analysis libraries, the findings showed a significant mismatch, with Kingmaker's classifications, only achieving a 38% accuracy rate. This low accuracy, coupled with inept dashboard, led to time, money, and human energy wasted; While recklessly misleading the volunteer force. Further scrutiny into Kingmaker's structure revealed a lack of any data science professionals and connections to a fake company, "Goldfish Code," raising concerns about data integrity and operational transparency. Strikingly, Kingmaker has no business licenses to operate. The Kingmaker Data founder: Matthew Woolbright, refuses to answer basics questions as they relate to safety and quality. The results support the null hypothesis, indicating no substantial evidence of machine learning, and suggest that Kingmaker's classifications are likely randomized, leading to serious misclassifications that put volunteers at risk. This study emphasizes the urgent need for consumer protection and regulation in political data services, advocating for standards that ensure data accuracy, transparency, and accountability to protect volunteer safety and public trust.

Research Questions:

1. Is there evidence of a machine learning model?
2. What is the accuracy of Kingmaker's political sentiment classifications?

Null and Alternative Hypotheses

- **Null Hypothesis (H_0):** There is no evidence of machine learning.
- **Alternative Hypothesis (H_1):** There is evidence of machine learning.
- **Null Hypothesis (H_2):** The political sentiment classifications are no more accurate than random chance or do not significantly match the "true classifications" from the county dataset.
- **Alternative Hypothesis (H_3):** The political sentiment classifications significantly match the "true classifications" from the county dataset, indicating the model is accurate in predicting political sentiment.

Context:

The following is a big data classification study establishing a baseline on which any political entity can test a data vendor's political identification predictions against the Washington State voter census data. The contribution of this study to the fields of Safety, AI Ethics, and Consumer Awareness, is to explore Kingmaker's political sentiment classification accuracy. With this industry information, policymakers can propose legislation to prevent dubious vendors; Maximizing the investment put into political data platforms and enhancing the safety of the volunteer force. An article titled, *Effective Black Box Testing of Sentiment Analysis Classification Networks*, showcases a study testing classification strength using the identical variables of 'predicted sentiment labels' and 'true sentiment' (UT, 2016). Another article named: *Comparative Study on Machine Learning Algorithms for Sentiment Classification*, uses similar variables to explore political sentiment predictions generated from machine learning; They found that these variables are key factors in overall testing relevance (UiB, 2018). Understanding these variables can help describe the relationship between the independent variables and dependent variables. Additionally, with Kingmaker data, we can inspect the raw dataset for evidence of machine learning. Supported by Oliver Bartlett's article, *How to prove the value of machine learning and avoid worthless models*, covering basic testing concepts to confirm precision (Dataparq, 2021).

Safety- Political canvassing a stranger's door in an aggressively polarized nation can be scary. Therefore, all steps of prior proper planning must be premeditated before politically engaging with strangers on their doorsteps (thewomencampaign, 2021). Volunteers want to be safe and save time, so they rely on data driven decisions. When volunteers have traumatic experiences, cold approaching doors based on data; They lose faith, waste time, and are reluctant to volunteer (Roupenian, 2018).

A copy of the python code to replicate this analysis can be found here:

https://github.com/Bloomingbiz/Blog_codes/blob/main/Kingmaker%20Data%20Exploration.ipynb

Data and Data Gathering:

Initially, five datasets were procured for this analysis, one from Spokane County and four from Kingmaker. The county dataset, is a political party census dataset, made available via the Washington Secretary of State and disseminated to the individual counties.

The county dataset contains 134,667 instances, of these instances 78,294 are notorious republican and 53,777 are notorious democrat voters; The instances have been proven by the voter, with the outside indicated party marked on the outside of the ballot; Again, verified by the state via inspecting the corresponding party indicated on the ballot. If the party marked on the outside of the envelope did not match the ballot party, then the ballot was discarded from the analysis. The remaining rows without the stated party affiliation are dropped from the analysis.

Limitations- "independent" sentiment won't be factored into the analysis due to the low population proportion. In the end state, even if independents were factored in and hypothetically scored 100% accuracy, it would prove to be underfit to independents only and not increase the average to a reliable number.

The Kingmaker data was provided by the Washington State GOP via subscription; The four datasets provided are named after the labeled sentiment classification: “strong republican” (44,053 rows), “likely republican” (10,777 rows), “strong democrat” (36,699 rows), and “likely democrat” (57,244 rows). The datasets were outputted as a downloadable .csv file after selecting all instances for a given party from the Kingmaker platform.

The dataset is limited to only Spokane County. Though the datasets have multiple columns for possible exploration of all instances, only “Party” will be germane to the analysis since it contains the verified label for the entire voter instance. From this variable, we split of the county dataset into two separate sets based on ‘Notorious Republican’ or ‘Notorious Democrat’ party indication.

The following is a list of variables from the county data:

'Ballot ID', 'Voter ID', 'County', 'First Name', 'Last Name', 'Gender',
'Election', 'Ballot Status', 'Challenge Reason', 'Sent Date',
'Received Date', 'Address', 'City', 'State', 'Zip', 'Country', 'Split',
'Precinct', 'Return Method', 'Return Location', 'Party'

The following are a list of variables for all Kingmaker data:

'lal_voter_id', 'vu_id', 'user_id', 'first_name', 'middle_name',
'last_name', 'address', 'city', 'city_mailing', 'zipcode', 'state',
'phone1', 'phone2', 'precinct', 'turnout_prediction', 'contact_visit',
'contact_call', 'contact_text', 'contact_digital', 'contact_mail',
'support_status', 'tags', 'contact_visit_count', 'contact_call_count',
'contact_text_count', 'contact_digital_count', 'contact_mail_count',
'top_issue'

From the above variables, the only variable germane to this analysis is “Voter ID”. Moreover, Kingmaker’s ‘vu_id’ is the Washington State “Voter ID”, encoded with simple “WAO” identifier preceding the 8-digit number. Additionally, the remaining Kingmaker variables are too sparse to be considered for any serious machine learning model classifications or predictions. Given Kingmaker’s stated variables, it is *not scientifically possible* to conduct any accurate sentiment classification. Sentiment cannot be forecasted based on a ‘name’ and ‘address’. The phone numbers may not be correct. For example, the variable, ‘turnout_prediction’ is based on unknown variables. Most of the ‘contact_’ variables are 95% filled with ‘o’s or missing values; Same for ‘Support_Status’, ‘tags’, and ‘top_issue’. Also indicating that the Kingmaker database is not updating with canvassing app: “Block Walker”, wasting all the data collected from the volunteers.

Glaringly, the Kingmaker Data platform offers no product user-manual or explanations. Another red flag is when inspecting the variable sparsity. The below visualization showcases the variable sparsity’s per the Kingmaker datasets.

lal_voter_id	0.000000	Kingmaker Likely Republicans	lal_voter_id	0.000000	Kingmaker Strong Republicans
vu_id	0.000000		vu_id	0.000000	
user_id	0.000000		user_id	0.000000	
first_name	0.000000		first_name	0.000000	
middle_name	9.186230		middle_name	11.848823	
last_name	0.018558		last_name	0.004839	
address	0.000000		address	0.000000	
city	0.083511		city	0.056861	
city_mailing	9.937831		city_mailing	5.745360	
zipcode	0.176301		zipcode	0.114931	
state	0.018558		state	0.022986	
phone1	59.831122		phone1	69.649641	
phone2	77.795305		phone2	61.350384	
precinct	0.027837		precinct	0.085896	
turnout_prediction	0.000000		turnout_prediction	0.001210	
contact_visit	96.872970		contact_visit	96.387524	
contact_call	0.612415		contact_call	0.597643	
contact_text	74.705391		contact_text	64.847928	
contact_digital	84.225666		contact_digital	74.375136	
contact_mail	0.612415		contact_mail	0.597643	
support_status	95.768767		support_status	95.011977	
tags	26.797810		tags	17.341334	
contact_visit_count	0.018558		contact_visit_count	0.015727	
contact_call_count	0.000000		contact_call_count	0.001210	
contact_text_count	0.000000		contact_text_count	0.000000	
contact_digital_count	0.000000		contact_digital_count	0.000000	
contact_mail_count	0.000000		contact_mail_count	0.000000	
top_issue	98.626705		top_issue	98.175615	
top_issue	98.626705		Unnamed: 28	99.997588	

lal_voter_id	0.000000	Kingmaker Likely Democrats	lal_voter_id	0.000000	Kingmaker Strong Democrats
vu_id	0.000000		vu_id	0.000000	
user_id	0.000000		user_id	0.000000	
first_name	0.000000		first_name	0.000000	
middle_name	9.186230		middle_name	11.468977	
last_name	0.018558		last_name	0.008175	
address	0.000000		address	0.000000	
city	0.083511		city	0.049048	
city_mailing	9.937831		city_mailing	6.425243	
zipcode	0.176301		zipcode	0.253413	
state	0.018558		state	0.002725	
phone1	59.831122		phone1	69.132674	
phone2	77.795305		phone2	68.898335	
precinct	0.027837		precinct	0.000000	
turnout_prediction	0.000000		turnout_prediction	0.000000	
contact_visit	96.872970		contact_visit	99.457751	
contact_call	0.612415		contact_call	0.673043	
contact_text	74.705391		contact_text	99.700264	
contact_digital	84.225666		contact_digital	99.307883	
contact_mail	0.612415		contact_mail	0.673043	
support_status	95.768767		support_status	99.215237	
tags	26.797810		tags	11.842285	
contact_visit_count	0.018558		contact_visit_count	0.002725	
contact_call_count	0.000000		contact_call_count	0.000000	
contact_text_count	0.000000		contact_text_count	0.000000	
contact_digital_count	0.000000		contact_digital_count	0.000000	
contact_mail_count	0.000000		contact_mail_count	0.000000	
top_issue	98.626705		top_issue	99.411428	

From the above dataset variables and sparsity percentages, it appears that there was *no data cleaning process*. According to an article titled: *Data Cleaning in the Process Industries*, had there been a machine learning model, the variable sparsity should be ‘0’, as per the industry standard data cleaning for machine learning (ResearchGate, 2015). Given the variables, it appears that the Kingmaker has failed to conduct data cleaning, fundamental to serious statistical analysis.

Data Analytics Tools and Techniques:

Overall, this is an exploratory quantitative data analytic technique and a descriptive statistic. The tools used will be Jupyter Notebook operating in Python code, running statsmodel api as a reliable open-source statistical library. Due to the data size, a Pandas data frame will be called, same with Numpy. Next, the Kingmaker variable “vu_id” will be parsed, separating the preceding “WAO” from the remaining state-issued-8-digit-voter-id-number; Secondly, creating an additional column called “Voter ID”. At this point, both the county and Kingmaker datasets will have the identical column “Voter ID”, containing the parsed Washington State issued voter identification number. Secondly, the *merge()* function is necessary for this analysis because, “the method updates the content of two data frames, merging them together, using the specified column” (W3Schools, 2024). After merging, the final datasets are combined instances of only rows with matching “Voter ID”.

Justification of Tools/Techniques:

Python will be used for this analysis because Numpy and Pandas packages can manipulate large datasets (IBM, 2021). The tools and techniques are common industry practice and have consensus of trust. The technique is justified through the variable necessary to match between the stated datasets. In so doing, may just reveal different modes of frequency distribution. Because of the size of the dataset, pandas and Numpy will be called. Python is being selected over SAS because the Python has better visualizations and more access to premiere statistical libraries (Panday, 2022).

Project Outcomes: To find evidence of machine learning and test the accuracy of the political sentiment classification outputs, the proposed end state is a basic descriptive statistical test that can compare the Kingmaker's integrity to the targeted groups (UiB, 2019). Lastly, a copy of the Jupyter Notebook with the Python code will be available; Additionally, the data will be submitted to the appropriate state / federal agencies and made available upon request (from authorized entities). According to the same study on 'black box sentiment scoring', exploratory testing was instrumental in support for alternative hypothesis, against other categorical variables. (UT, 2016).

The following visualizes how the study is conducted:

The Analysis

- Six datasets were compared, four from Kingmaker and the 3/2024 Spokane County Match-back data indicating the party.



- The four datasets from Kingmaker are labeled:

Strong Republican

Likely Republican

Strong Democrat

Likely Democrat

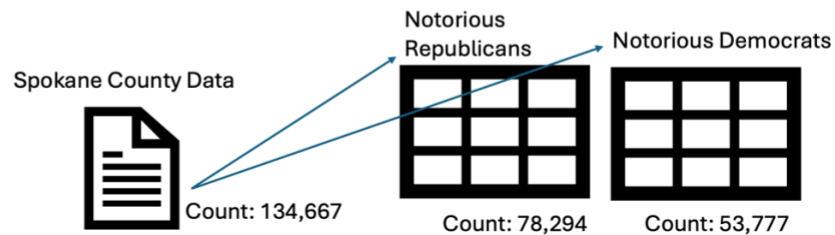


The Analysis

From the county dataset, two separate sets were derived: “Notorious Republicans” and “Notorious Democrats”.

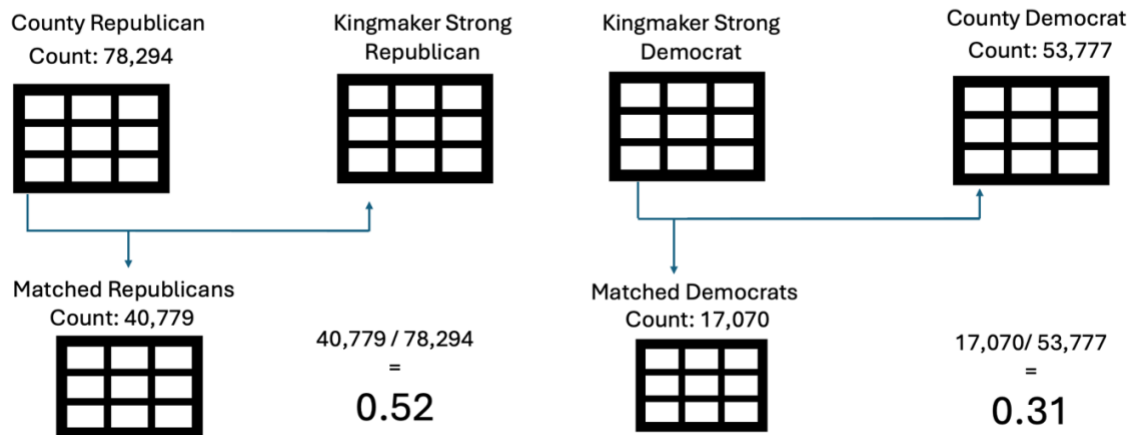
At this point, a total of 6 sets were procured.

The two sets from each party are compared for matching variable “Voter ID”.



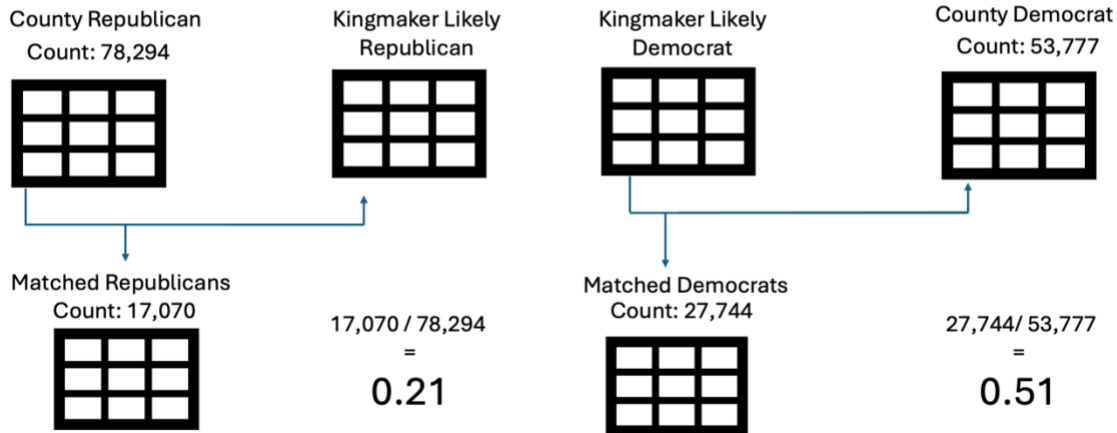
The Analysis

- The compared datasets from each party are merged into a final list containing a count of all the matching rows / instances.



The Analysis

- The compared datasets from each party are merged into a final list containing a count of all the matching rows / instances.



Kingmaker Accuracy

Strong Democrat Accuracy	Likely Democrat Accuracy	Likely Republican Accuracy	Strong Republican Accuracy
0.31	0.51	0.21	0.52

$$0.31 + 0.51 + 0.21 + 0.52 = 1.55$$

$$1.55 / 4 = 0.38$$

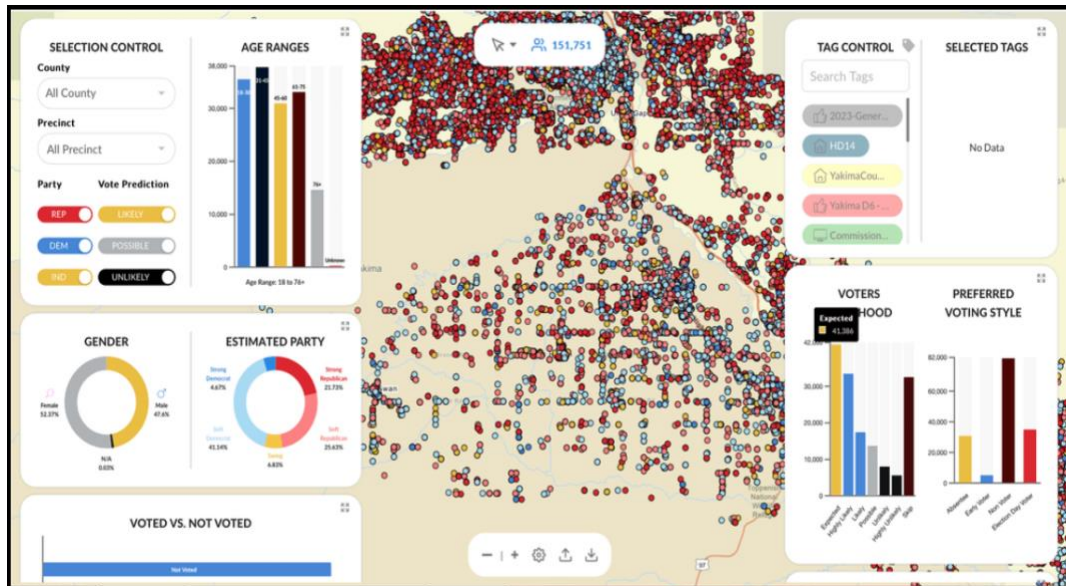
38% Total Accuracy

Given the 38% accuracy with the census data, the entire Kingmaker classification system accuracy is worse than a coin flip. According to the article, *Overcoming the pitfalls and perils of algorithms: A classification of machine learning biases and mitigation methods*, Kingmaker would be considered “overfit” with too much training data and unable to generalize well on unseen data (Journal of Business Research, 2022); If there was a machine learning model. Problematically leading to unethical data products like, *The Racist Soap Dispenser* (Civics of Tech, 2018). However, there is no evidence of a machine learning model. Given these findings, it implies that Kingmaker simply “randomized” the sentiment labels for ‘likely republican’, ‘likely democrat’, and ‘strong democrat’.

Now exploring the Kingmaker Dashboard:

The below image is sourced from kingmakerdata.com.

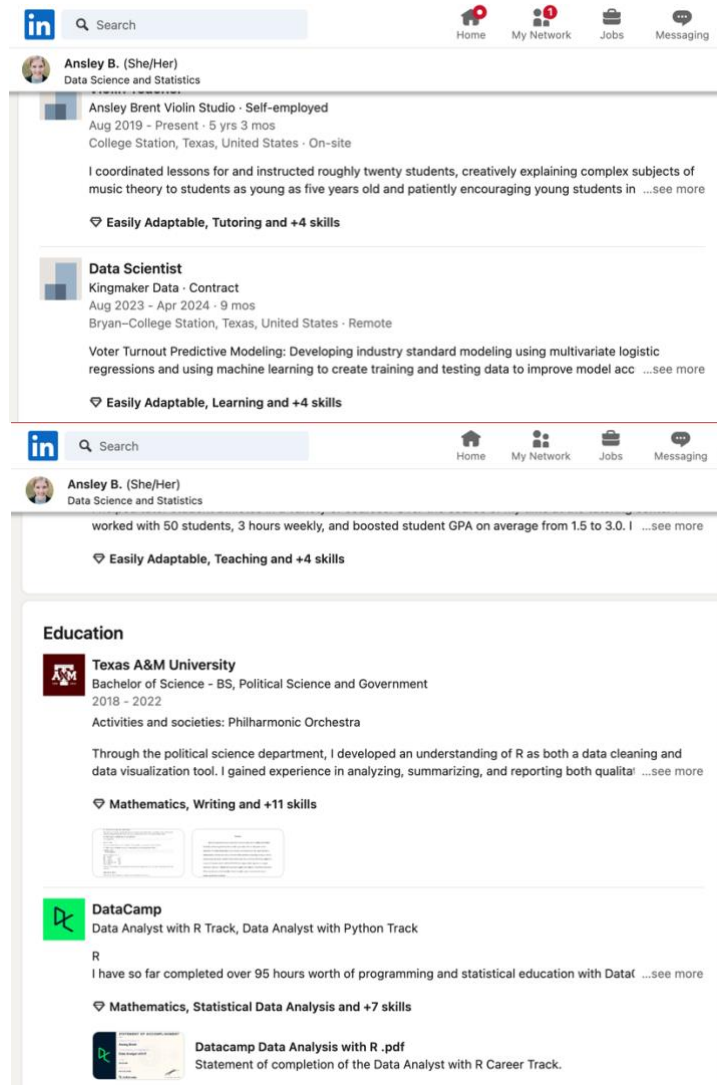
When it comes to the entire Kingmaker Data product, what you see is what you get; A low-budget clunky dashboard populating with bamboozlingly visualizations. Akin to what a *lazy - student* would make as a *first dashboard assignment*. The control tags don't work for the end-user. Graphs are hard to interpolate and given the accuracy, it's all worthless.



Numerous volunteers have expressed frustrations and only use Excel with downloaded csv files generated from selecting the “Party” and “Vote Prediction” toggles. At that point, the center screen allows for a csv file download (bottom center of the screen); From that the sentiment classifications datasets are generated for exploration.

Now exploring how Kingmaker was made:

Kingmaker has no data scientist, and the only alleged ‘data scientist’ quit in April 2024. Below is a picture of LinkedIn profile for “Ansley B”. Ansley B. maybe a fake profile, either way, she is woefully unqualified to be a data scientist given her education and experience. However, that is the general motif of Kingmaker, faux. The founder of Kingmaker Data is Mathew Woolbright, a former journalist. Kingmaker was possibly produced by another company called Goldfish Code. Kingmaker Data is not a recognized company in Washington State or Texas; Searchable only through Google and dead-end / unactive social media profiles.



The above image is from 'Ansley B.', the alleged data scientist. Notably, a *bachelor's in political science* does not make someone a data scientist or qualified in statistics; Online data camps are not proof-of-expertise or being 'held to a standard'. However, shell-companies are rarely held to a standard because they are under the radar, including criminals.

Looking closer, Kingmaker is a fake company founded and exclusively operated by Mathew Woolbright. In the picture below, Woolbright alleges that "Goldfish Code," created the Kingmaker platform. The below screenshot is from a Kingmaker promotional YouTube video on the Goldfish Code YouTube channel. Beside short testimonials videos, the *Goldfish Code* YouTube channel is sparse, with no real evidence of producing anything.



The Kingmaker Data website is represented with a Texas phone number but no actual address. Concurrently, there is no record of a business containing the string “KINGMAKER” or “Mathew Woolbright” in any spelling, combination, or capitalization. Indicating that **Kingmaker has no business license to operate in Texas.**

← → ↺ webservices.sos.state.tx.us/filing-status/status.aspx

Texas Secretary of State
Jane Nelson

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Business Filing Tracker (submitted last 6 months)

Documents will appear on the filing status list once they have been entered into the system. For documents submitted by mail, fax, or personal delivery, it generally takes at least one business day from the time a document has been submitted to the office for the document to be entered into the system and show a status of Received.

All or part of Entity Name:

No entries found for the entity name provided

Hint: Try the search again with one word of the entity name, or with fewer characters

According to the Washington Secretary of State, there is no business entity called ‘Kingmaker Data’ or ‘Mathew Woolbright’ (any spelling or capitalization). Indicating that **Kingmaker Data has no business license to operate in Washington State or Colorado.**

Business Search

BUSINESS SEARCH RESULTS

Business Name	UBI#	Business Type	Principal Office Address	Registered Agent Name	Status
KING MAKER CREDIT REPAIR LLC	604 815 432	WA LIMITED LIABILITY COMPANY	309 PARK PL, EVERETT, WA, 98203-2022, UNITED STATES	GUY K BERNSTEIN	ADMINISTRATIVELY DISSOLVED
KING MAKER GAMES LLC	603 409 679	FOREIGN LIMITED LIABILITY COMPANY		ERIC J SEXTON	TERMINATED
KING MAKER MARKETING, INC.	602 637 125	FOREIGN PROFIT CORPORATION	1304 ANNAPOLIS DR, RALEIGH, NC, 27608	COGENCY GLOBAL INC	TERMINATED
KING MAKER TECHNOLOGIES, INC	603 355 174	WA PROFIT CORPORATION	11029 14TH AVE NE, SEATTLE, WA, 98125, UNITED STATES	ROY PARANGOT	ADMINISTRATIVELY DISSOLVED
KINGMAKER ADVISORY LLC	605 536 281	WA LIMITED LIABILITY COMPANY	1631 GRANT AVE # 3750, BLAINE, WA, 98230-5161, UNITED STATES	ABHIJIT CHHABRA	ACTIVE
KINGMAKER KARES	603 258 160	WA NONPROFIT CORPORATION	22700 30TH AVE S A-207, DES MOINES, WA, 98198, UNITED STATES	KENNETH TAYLOR	ADMINISTRATIVELY DISSOLVED
KINGMAKER SOLUTIONS, LLC	605 570 463	WA LIMITED LIABILITY COMPANY	12224 NE BEL RED RD UNIT 2029, BELLEVUE, WA, 98009-2231, UNITED STATES	ANN MOLITOR	ACTIVE
KINGMAKERS GROUP LLC	604 410 835	WA LIMITED LIABILITY COMPANY	950 VIA KACHESS RD., EASTON, WA, 98925, UNITED STATES		VOLUNTARILY DISSOLVED
KINGMAKERS INC. DBA KINGMAKERS WA INC.	604 490 763	FOREIGN PROFIT CORPORATION	100 S KING ST. STE. 100, SUITE 746, SEATTLE, WA, 98104, UNITED STATES	KYLON GIENGER	WITHDRAWN
KINGMAKERS, LLC	603 178 218	WA LIMITED LIABILITY COMPANY	17109 W BIG LAKE BLVD, MOUNT VERNON, WA, 98274-8375, UNITED STATES	RICHARD HOAG	ADMINISTRATIVELY DISSOLVED

sos.state.co.us/ucc/pages/biz/bizSearch.xhtml

Colorado Secretary of State Jena Griswold

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Instructions

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Login

Create User Account

Business Search Result

Select the business organization ID for detailed information and to confirm.

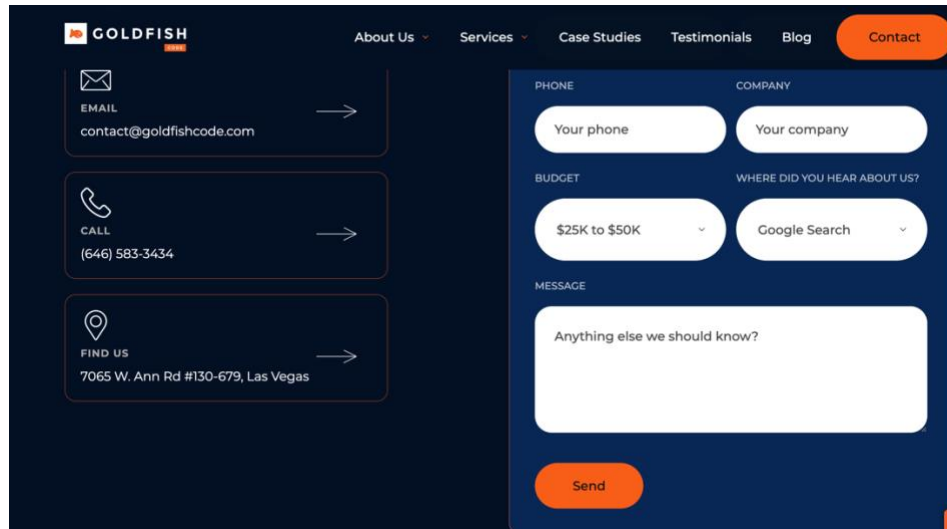
(1 of 1) << < 1 > >>

ID #	Name ↑↓	Address
20181389277	Kingmaker Energy, Inc.	575 Union Boulevard, Suite 305, Lakewood, CO, 80228, United States
20201894312	KINGMAKER INDUSTRIES, LLC, Dissolved April 7, 2021	910 16th St #1200, Denver, CO, CO, 80202, United States

(1 of 1) << < 1 > >>

New Search Cancel & Return

Let's explore Goldfish Code, the software development team behind Kingmaker. The below picture is of the Goldfish Code contact page:



GOLDFISH CODE

About Us Services Case Studies Testimonials Blog [Contact](#)

EMAIL
contact@goldfishcode.com →

CALL
(646) 583-3434 →

FIND US
7065 W. Ann Rd #130-679, Las Vegas →

PHONE
Your phone

COMPANY
Your company

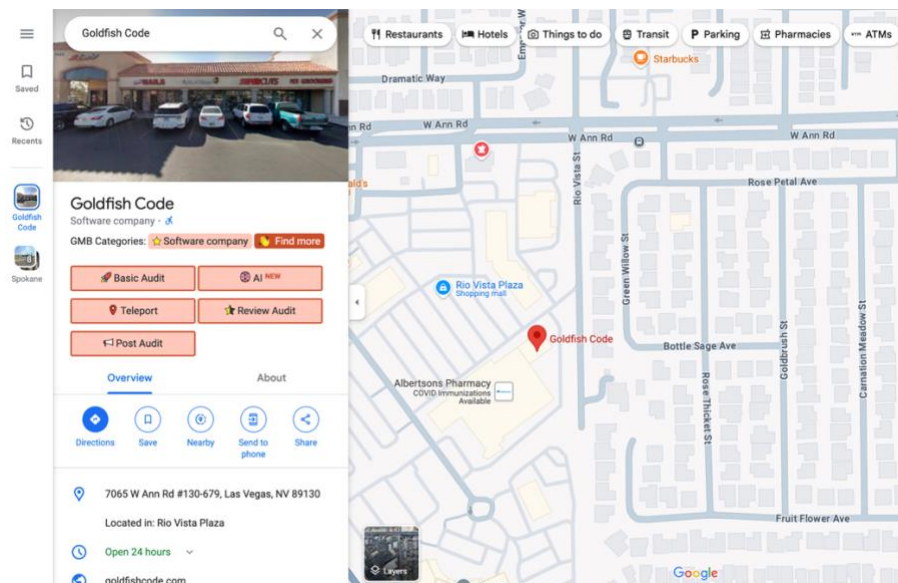
BUDGET
\$25K to \$50K

WHERE DID YOU HEAR ABOUT US?
Google Search

MESSAGE
Anything else we should know?

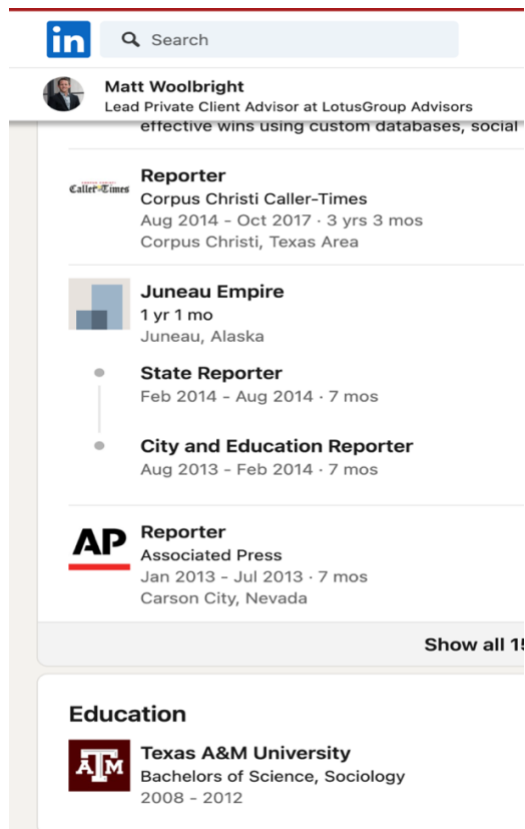
[Send](#)

Like Kingmaker, *Goldfish Code* is also a fake company with no real employees or proof of serious professionalism. The contact number is for New York, NY; We have reached out numerous times to Goldfish Code and have received no response. Additionally, the Goldfish Code address is suspect as it is between #130 – 679. When inspecting that address, it turns out to be a strip mall in Las Vegas, NV (as per the photo below). In the photo of the mail there is no sign for ‘Goldfish Code’.



The image below is from Woolbright’s LinkedIn page. Woolbright has no technical degree or background. His only degree is in sociology, made evident given the verbiage he uses to when expressing his product to a more technical audience. His only alleged professional development

was journalism. Strangely, Woolbright doesn't even promote his own company, "Kingmaker" on LinkedIn.



Instead, Woolbright claims to work for *LotusGroup Advisors*. LotusGroup Advisors is another fake company with no power to operate. According to the Security and Exchange Commission (SEC), LotusGroup Advisors has no authorization to operate since 2017. Woolbright claims to live in Colorado, but represents Kingmaker Data with a Texas phone number.



adviserinfo.sec.gov/firm/summary/143379

Investment Adviser Search

Investment Adviser Data

Resources

FORM ADV

Registration/Reporting Status

Part 2 Brochures

View Form ADV By Section

Accountant Surprise Examination Report

INDIVIDUAL FIRM

Individual Name/CRD# at Firm Name or CRD/SEC# (optional) in City, State or ZIP (optional) SEARCH

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Investment Adviser Firm Summary

LOTUSGROUP ADVISORS (CRD # 143379/SEC#:801-111051)
 LOTUSGROUP ADVISORS, LOTUSGROUP ADVISORS, LLC

VIEW LATEST FORM ADV FILED PART 2 BROCHURES PART 3 RELATIONSHIP SUMMARY

The adviser's **REGISTRATION** status is listed below.

REGISTRATION STATUS		
SEC / JURISDICTION	REGISTRATION STATUS ⓘ	EFFECTIVE DATE
SEC	Approved	8/28/2017
California	Terminated	9/28/2017
Colorado	Terminated	8/30/2017
New York	Terminated	8/29/2017
Texas	Terminated	8/29/2017
Washington	Terminated	11/16/2015

When it comes to customer service, what is alarming, is how Woolbright is slow to respond, giving vague answers; Refusing to answer basic questions of data product consumer rights (Federal Trade Commission, 2020).

The following pictures are from the email chain maintained with Woolbright and the Spokane GOP volunteers. Notice how Woolbright continues to put his product “in a black box” (UT, 2016). Responding with vague answers to simple questions and attempting to delay until “after the election”. Keep in mind that the Kingmaker Data contains no variables about consumer behavior or past election participation.

Sarah Hawkins Oct 31, 2024, 8:23 AM (9 days ago) ☆ 😊 ↩ ⋮
to John, Mjbolt356, Lyledach, Jillianroseivey, Rob, Tim, Staci, me, Matt ▾
Jill? Matt?

Can you please identify where the party classification comes from
...

Matthew Woolbright Oct 31, 2024, 9:30 AM (9 days ago) ☆ 😊 ↩ ⋮
to Sarah, John, Mjbolt356, Lyledach, Jillianroseivey, Rob, Tim, Staci, me ▾
Hey Sarah,

I apologize, as you can imagine it's a pretty busy season for us! The party is based heavily on primary performance, but consumer factors come into a play when that's not a driving reference point (for example, limited or no primary behavior). We have a pretty complex machine learning model that generates those predictions and then back tests against prior year returns on the precinct level.

I'm happy to get on a call with you after the election and get into greater detail.
...



michael segaline <mbsegaline@gmail.com> Oct 31, 2024, 11:29 AM (9 days ago) ☆ 😊 ↩ ⋮
to Matthew ▾
Matthew,

Since you have a "complex machine learning model", what is the model you used and how did you, test / train that model? Where are the model scores?
...

Matthew Woolbright Oct 31, 2024, 12:21 PM (9 days ago) ☆ 😊 ↩ ⋮
to me ▾
Hey Michael,

After the election I'd be happy to help you with any modeling or data analysis you're working on and give some feedback if that would be beneficial for you. Given that our processes and models are pretty central to our business, that's not something I can give alot of detailed insight into. I hope you understand!
...



michael segaline <mbsegaline@gmail.com> Oct 31, 2024, 1:21 PM (9 days ago) ☆ 😊 ↩ ⋮
to Matthew ▾
Answer the questions.
...



Matthew Woolbright

to MJ, me ▾

Oct 31, 2024, 1:27 PM (9 days ago)



Hey Michael,

Respectfully, I will not be answering those questions on my company's methods, technology or models.

If you have insight you'd like to make sure we're considering, as I'm very confident you are just wanting to make sure Spokane County Republicans have the best chances possible of winning races, I'd be happy to discuss your ideas.

Best of luck this weekend!





Matt Woolbright
Founder and CEO
Cell - 361.834.6181
www.kingmakerdata.com



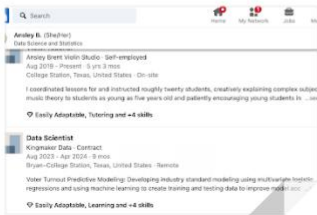
michael segaline <mbsegaline@gmail.com>

to Matthew ▾

No, you need to prove things to people. Is / was this your data scientist?



One attachment • Scanned by Gmail ⓘ



Matthew Woolbright

to me ▾

Have a good day, Michael.





Matt Woolbright
Founder and CEO
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In final analysis

- We **accept** the Null Hypothesis (H_0): There is **no evidence of machine learning**.
- We **reject** the Alternative Hypothesis (H_1)
- We **accept** the Null Hypothesis (H_2): The political sentiment **classifications are no more accurate than random chance** or do not significantly match the "true classifications" from the county dataset.
- We **reject** the Alternative Hypothesis (H_3)

The United States is aggressively divided politically; With a high likelihood of violence, **neighborhood canvassing is dangerous**. It can be scary to knock on a stranger's door in general, let alone promote politics. With an **accuracy score of 38%**, Kingmaker's sentiment classifications are *worse than a coin flip*. Additionally, **sentiment classification is impossible** given the variables that Kingmaker provides. The data our volunteers collected was wasted and not updated in the database. At the same time, the state census data is 100% accurate and the baseline for testing. Secondly, Kingmaker is a **fake company** operated by, Mathew Woolbright; While working for another fake company *LotusAdvisor Group*. Kingmaker was possibly developed and promoted by another shell company *Goldfish Code*. Equally, Kingmaker has **no team of data experts**, or anyone even qualified to do the job. There exists **no record of a business license** in both Texas and Washington. The **dashboard is useless** to the end-users. To emphasize, Kingmaker Data **offers no product user-manual** for reference or explanation.

Kingmaker has **no chain-of-custody on data or documentation** of the scientific method; Additionally, Woolbright **refuses to answer basic questions** about the scientific method and lies about his product. Glaringly, Woolbright is not forthcoming to basic questions of consumer safety. Moreover, **Woolbright used his sociology degree to social-engineer money away**, at the same time putting good volunteers in harms way. Now that the Kingmaker has no clothes, **these findings serve as a roadmap for consumer protection** against baseless analytics and classifications. Correspondingly, this intelligence serves as **definitive evidence of election tampering and fraud**. Lastly, this report works as merit to be submitted to the appropriate state and federal enforcement agencies.

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