

Unit Warscroll:



• WARSCROLL •

Orruk Brutes 🔖

Charging into battle with joyous bellows, Brutes seek out the largest enemies to batter into submission. Wearing the thickest armour and wielding huge weapons, they enjoy nothing more than dishing out a good and proper bashing.

MELEE WEAPONS	Range	Attacks	To Hit	To Wound	Rend	Damage
Brute Choppas	1"	4	3+	3+	-1	1
Jagged Gore-hacka	2"	3	3+	3+	-2	1
Gore-choppa	2"	3	4+	3+	-2	2
Boss Choppa	1"	3	3+	3+	-1	2
Boss Klaw and Brute Smasha	1"	4	4+	3+	-1	2

PITCHED BATTLE PROFILE &

Unit Size: 5 Points: 140 Battlefield Role: Battleline Base size: 40mm

Each model in an Orruk Brutes unit is armed with 1 of the following weapon options: Brute Choppas; or Jagged Gore-hacka. All models in the unit must be armed with the same weapon option. 1 in every 5 models can replace their weapon option with a Gore-choppa.

BATTALIONS: This warscroll can be used in

the following warscroll battalions:

- Brutefis
- Ironfist
- Weirdfist
- W Da Bossfist
- III Dakkbad's Brawl
- III Moggorz's Rekrootin' Krew

CHAMPION: 1 model in this unit can be a Brute Boss. Replace that model's weapon option with a Boss Choppa, or a Boss Klaw and Brute Smasha.

You Messin'?: Most beings with half an ounce of common sense swiftly wither under the furious gaze of an orruk Brute who has marked his territory.

Enemy models with a Wounds characteristic of 1 that are within 3" of this unit cannot contest objectives.

Duff Up da Big Thing: The Brutes of the Ironjawz excel at fighting and killing the most powerful foes.

Add 1 to hit rolls for attacks made by this unit that target a unit with a Wounds characteristic of 4 or more.



Unit Warscroll:



• WARSCROLL •

Blissbarb Archers %

Blissbarb Archers are the lowest class of Sybarite, but no less deadly for it. Even when running pell-mell across the field they fire with deadly accuracy, laughing with glee as their sharp and toxin-laced projectiles strike home.

MISSILE WEAPONS	Range	Attacks	To Hit	To Wound	Rend	Damage
Blissbarb Bow	18"	2	3+	4+	-1	1
MELEE WEAPONS	Range	Attacks	To Hit	To Wound	Rend	Damage
Sybarite Blade	1"	1	3+	4+		1

PITCHED BATTLE PROFILE &

Unit Size: 11 Points: 170 Battlefield Role: Battleline

MODEL BASE SIZE
Blissbarb Archers 28.5mm
Blissbrew Homonculus 25mm

Each model in a Blissbarb Archers unit is armed with a Blissbarb Bow and Sybarite Blade.

BATTALIONS: This warscroll can be used in the following warscroll battalions:

Depraved Carnival

CHAMPION: 1 model in this unit can be a High Tempter. Add 1 to the Attacks characteristic of that model's Blissbarb Bow. BLISSBREW HOMONCULUS: 1 in every 11 models in this unit must be a Blissbrew Homonculus. A Blissbrew Homonculus is armed with a Sybarite Blade. Add 1 to wound rolls for attacks made with missile weapons by this unit while it includes any Blissbrew Homonculi.

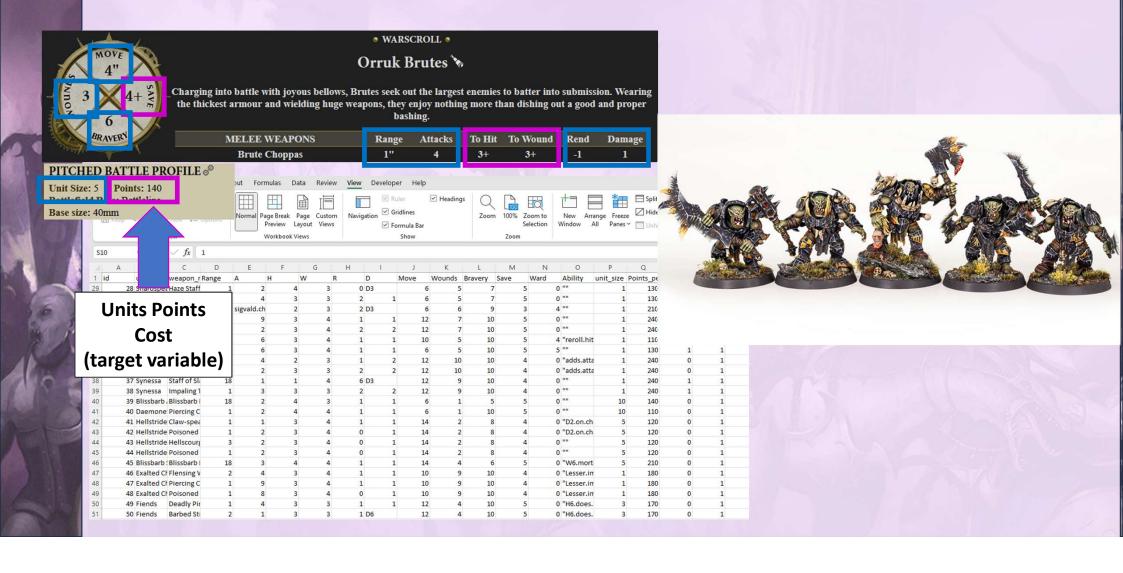
Light-footed Killers: Blissbarb Archers can deliver pinpoint shots even while cavorting wildly across the battlefield.

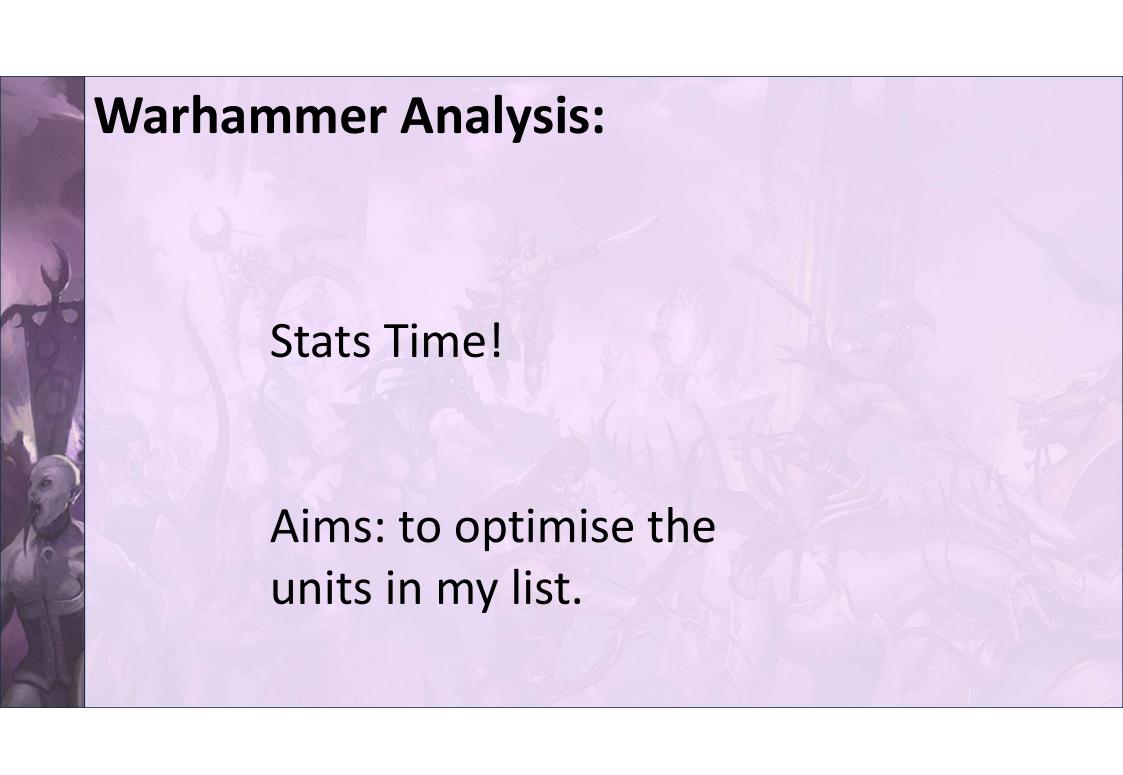
This unit can run and still shoot later in the turn.

EYWORDS CHAOS , HEDONITES OF SLAANESH , MORTAL , SLAANESH , BLISSBARB ARCHERS



Unit Warscroll:





Data Collection:

1) Attempted to pull data from Websites but alas the html was too dense. Therefore so manual processing was required (n = 172).

Data Cleaning:

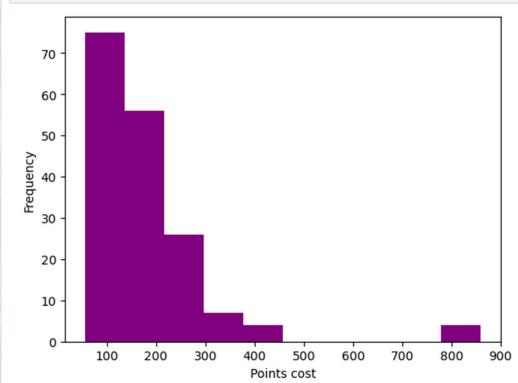
- Impute string values as relevant integers (e.g., D6 == 3.5).
- Invert dice roll values (not necessary but helpful to quickly interpret interactions).
- 3) Compute unit wounds by unit size features.

```
# Data Cleaning:
df = df.drop("id", axis = 1)
# Need to replace the string/chars with numeric.
def string replacer(x):
    x = x.replace("2D6", "7")
   x = x.replace("D3", "2")
    x = x.replace("3D6", "10.5")
   x = x.replace("D6", "3.5")
   x = x.replace("sigvald.charge", "7")
   x = x.astype(float)
    return(x)
# Need to the function to impute/fix string data points.
df["A"] = string replacer(df["A"])
df["W"] = string replacer(df["W"])
df["D"] = string replacer(df["D"])
df["Move"] = string replacer(df["Move"])
# Going to invert some of the features so that their coefs
# represent unit improvements (i.e., to-hit rolls on a 2+ are
# easier than to-hit rolls on a 4+ etc).
df["Save"] = 7 - df["Save"]
df["Ward"] = 7 - df["Ward"]
df["H"] = 7 - df["H"]
```

EDA:

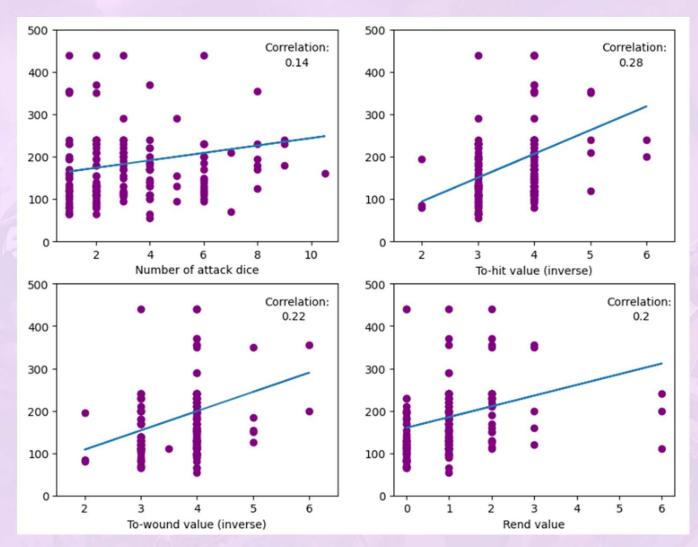
1) Examine feature histograms.

```
# Histogram of points costs.
plt.hist(df["Points_per_warscroll"], color="purple")
plt.xlabel("Points cost")
plt.ylabel("Frequency")
plt.show()
```



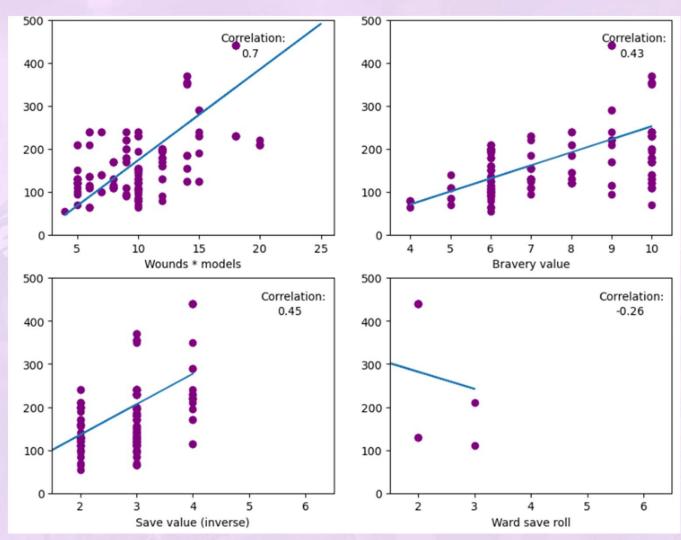
EDA:

2) Examine scatterplots between the target and features.



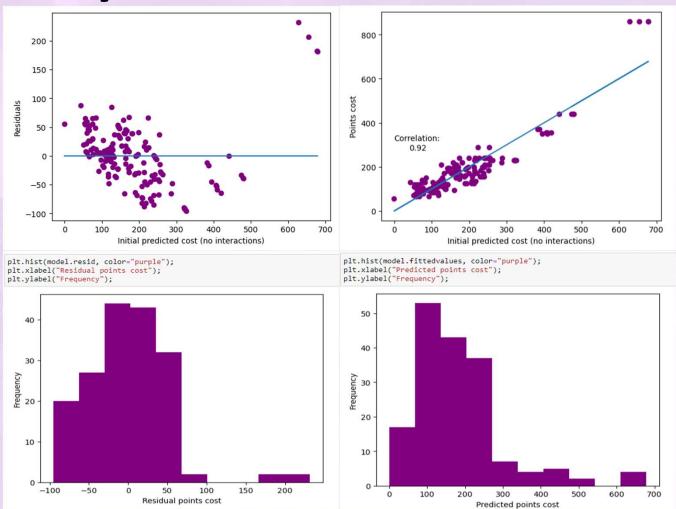
EDA:

2) Examine scatterplots between the target and features.



EDA:

- 3) Examine predicted values.
- 4) Examine residual values.
- 5) OLS assumptions etc.



EDA:

6) Examine initial regression model coefficients. #view model summary print(model.summary()) OLS Regression Results Dep. Variable: Points per warscroll R-squared: Model: Adj. R-squared: 0.826 Method: Least Squares F-statistic: 55.28 Date: Mon, 13 Nov 2023 Prob (F-statistic): 1.78e-54 Log-Likelihood: 12:00:26 -922.13 No. Observations: AIC: 1876. Df Residuals: 156 BIC: 1927. Df Model: 15 Covariance Type: [0.025 std err P> t -220.4718 55.006 -4.008 0.000 -329.125 -111.818 -0.0268 0.925 -0.029 0.977 -1.853 1.800 1.8087 2.604 0.695 0.488 -3.334 6.951 23.8283 8.532 2.793 0.006 6.975 40.682 -12.2390 8.995 -1.3610.176 -30.007 5.529 1.5733 5.609 0.280 0.779 -9.506 12,653 15.408 2.1816 6.696 0.326 -11.045 4.204 1.2435 1.499 0.830 0.408 -1.7179.619 Wounds 5.7168 1.975 2.894 0.004 1.815 Bravery 4.7949 3.743 1.281 -2.599 12.189 21.7656 6.301 3.454 9.319 34.212 Save 0.001 Ward 2.7065 3.545 0.764 -4.295 9.708 10.331 unit size 3.8115 3.301 1.155 0.250 -2.708 Spells 70.8970 7.129 9.945 0.000 56.816 84.978 slaanesh dummy -12.5517 13.205 -0.951 0.343 -38.636 13.532 17.774 Wounds X model 14.0543 10.335 Omnibus: Durbin-Watson: Prob(Omnibus): 0.000 Jarque-Bera (JB): 138.088 Skew: 1.144 Prob(JB): 1.03e-30 Kurtosis: 6.746 Cond. No.

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

EDA:

- Examine initial regression model coefficients.
- Solved issue with high-low wounds and model counts.

```
#view model summary
print(model.summary())
                              OLS Regression Results
                   Points per warscroll
                                           R-squared:
Model:
                                           Adj. R-squared:
                                                                             0.826
Method:
                           Least Squares
                                           F-statistic:
                                                                             55.28
                                           Prob (F-statistic):
                                                                          1.78e-54
Date:
                       Mon, 13 Nov 2023
                                           Log-Likelihood:
                                12:00:26
                                                                            -922.13
No. Observations:
                                           AIC:
                                                                             1876.
Df Residuals:
                                     156
                                           BIC:
                                                                             1927.
Df Model:
                                      15
                                                                  [0.025
                              std err
                                                      P> t
                                                                              0.9751
                -220.4718
                               55.006
                                          -4.008
                                                      0.000
                                                                -329.125
                                                                            -111.818
                   -0.0268
                                0.925
                                          -0.029
                                                      0.977
                                                                  -1.853
                                                                               1.800
                   1.8087
                                2.604
                                           0.695
                                                      0.488
                                                                  -3.334
                                                                               6.951
                                           2.793
                                                                  6.975
                                                                              40.682
                   23.8283
                                8.532
                                                      0.006
                  -12.2390
                                8.995
                                          -1.361
                                                      0.176
                                                                 -30.007
                                                                               5.529
                   1.5733
                                5.609
                                           0.280
                                                      0.779
                                                                  -9.506
                                                                              12,653
                                                                              15.408
                   2.1816
                                6.696
                                           0.326
                                                                 -11.045
                   1.2435
                                1.499
                                           0.830
                                                                  -1.717
                                                                               4.204
                                                      0.408
                                                                               9.619
Wounds
                   5.7168
                                1.975
                                           2.894
                                                      0.004
                                                                  1.815
Bravery
                   4.7949
                                3.743
                                           1.281
                                                                  -2.599
                                                                              12.189
                   21.7656
                                                                  9.319
                                                                              34.212
Save
                                6.301
                                           3.454
                                                      0.001
Ward
                   2.7065
                                3.545
                                           0.764
                                                                  -4.295
                                                                               9.708
                                                                              10.331
unit size
                   3.8115
                                3.301
                                           1.155
                                                      0.250
                                                                  -2.708
Spells
                   70.8970
                                7.129
                                           9.945
                                                      0.000
                                                                  56.816
                                                                              84.978
slaanesh_dummy
                 -12.5517
                               13.205
                                          -0.951
                                                                              13.532
                                                                              17.774
Omnibus:
                                         Durbin-Watson:
Prob(Omnibus):
                                         Jarque-Bera (JB):
                                                                         138.088
Skew:
                                         Prob(JB):
                                                                        1.03e-30
Kurtosis:
                                 6.746
                                         Cond. No.
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

Feature Engineering:

Standardise (or centre)

 variables and compute all 2 way interactions...

```
# Potential interaction effects to test.

# 2-way interactions.

df["A_X_H"] = preprocessing.scale(df["A"]) * preprocessing.scale(df["W"])

df["A_X_W"] = preprocessing.scale(df["A"]) * preprocessing.scale(df["W"])

df["A_X_D"] = preprocessing.scale(df["A"]) * preprocessing.scale(df["D"])

df["H_X_W"] = preprocessing.scale(df["H"]) * preprocessing.scale(df["W"])

df["H_X_D"] = preprocessing.scale(df["H"]) * preprocessing.scale(df["D"])

df["W_X_D"] = preprocessing.scale(df["W"]) * preprocessing.scale(df["D"])

# Join offensive interactions.

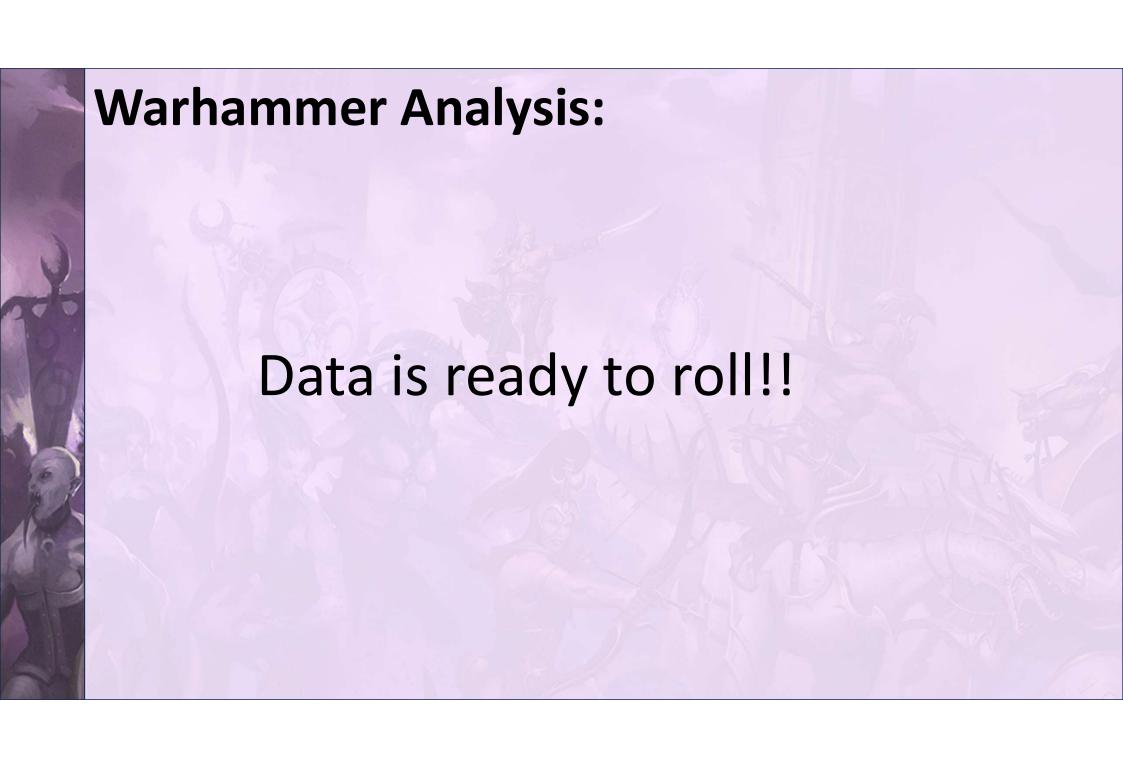
x = x.join([df["A_X_H"], df["A_X_W"], df["A_X_D"], df["H_X_W"], df["H_X_D"], df["W_X_D"]])

model = sm.OLS(dv, x).fit()
print(model.rsquared)
```

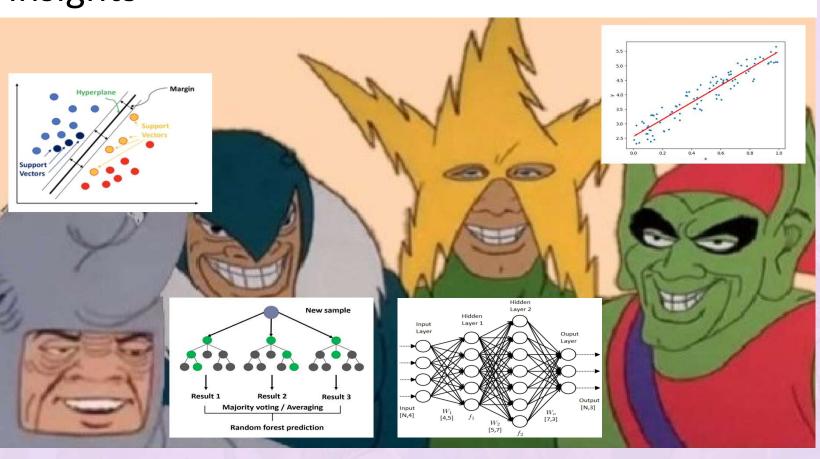
Feature Engineering:

1) ...and similarly for all 3-way and 4-way interaction effects

```
# Four-way effect.
df["all_damage"] = preprocessing.scale(df["A"]) * preprocessing.scale(df["H"]) * preprocessing.scal
# Four-way effect.
df["all_defence"] = preprocessing.scale(df["Wounds_X_model"]) * preprocessing.scale(df["Save"]) * p
df["damage_X_defence"] = df["all_defence"] * df["all_damage"]
x = x.join([df["all_damage"], df["all_defence"], df["damage_X_defence"]])
model = sm.OLS(dv, x).fit()
print(model.rsquared)
```

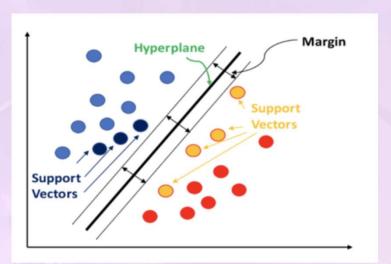


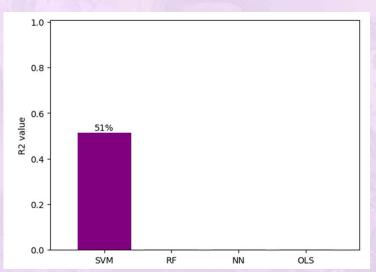
Me and the boys about to go find some insights



Support Vector Machines:

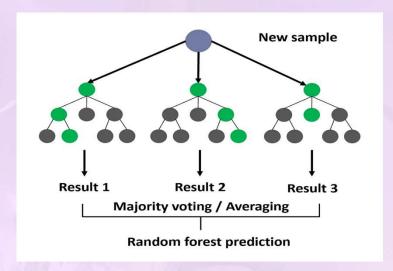
- Common non-linear classifier (but also apparently does regression). Will find optimal (hyper)plane to separate data.
- Maximizes margins between classes based on nearby datum.
- Will predict new inputs based on there location within margins.

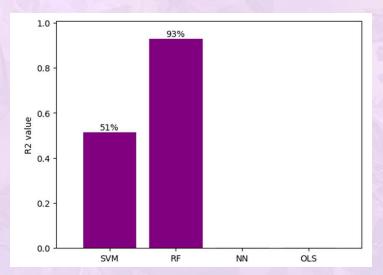




Random Forest Boi ™:

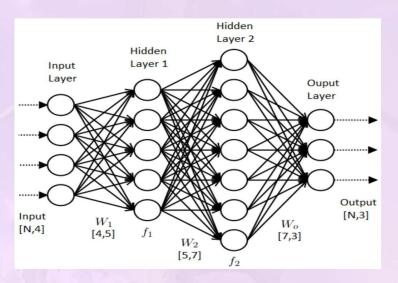
- Uses decision tree methods to classify cases.
- Each individual tree is a poor predictor, however when aggregated (bagging/boosted) results are more accurate.
- Uses random selection of predictor variables.

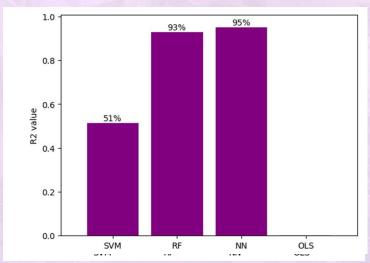




Neural Network:

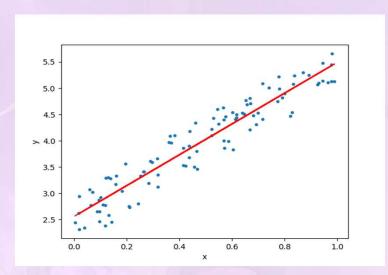
- Designed to mimic human synaptic processes.
- Networks contain input, hidden, and output layers.
- Each node adds weights and biases to the function. These forms an activation function.

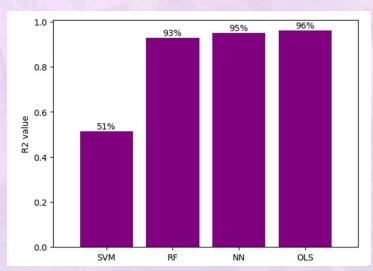


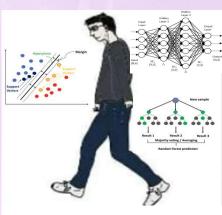


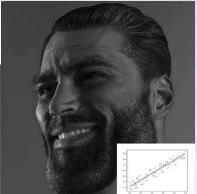
Linear Regression:

- Fits a line to the data using ordinary least squares.
- · Minimises residuals.
- Can be used to model continues target variables.



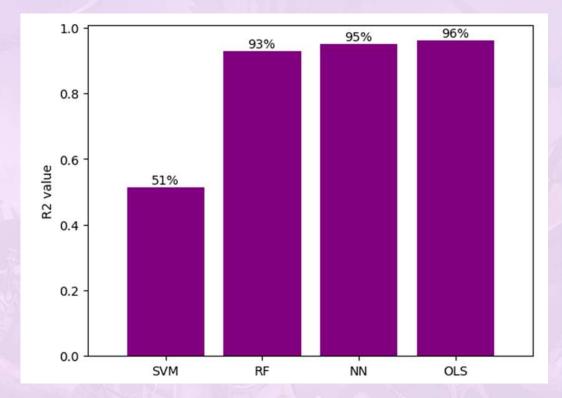


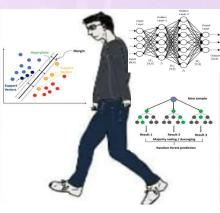




- Uses massive computing
- Is difficult to interpret
- Tuning is timeconsuming
- Is cringe
- Algos are still being optimised
- Requires massive data

- Can literally be calculated by hand
- coefs tell you how to interpret
- What are compute costs?
- Perfected by Gauss 1795
- Requires small samples
- Is the best linear unbiased est.

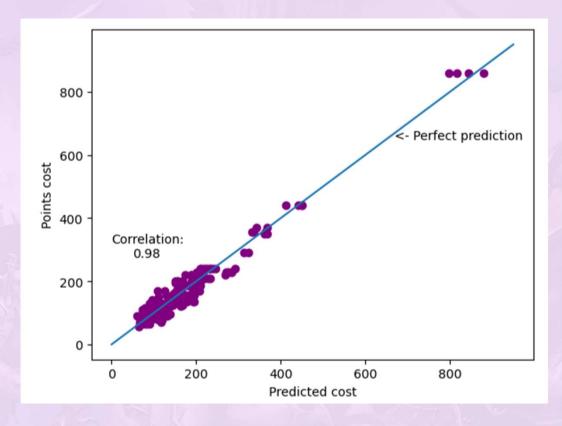


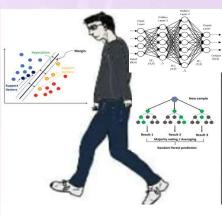


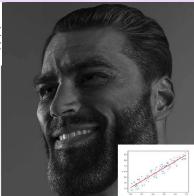
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OLS Regression Results

Dep. Variable:	Points_per_warscroll	R-squared:	0.961
Model:	OLS	Adj. R-squared:	0.950
Method:	Least Squares	F-statistic:	91.40
Date:	Sun, 12 Nov 2023	Prob (F-statistic):	2.33e-78
Time:	19:22:05	Log-Likelihood:	-802.52
No. Observations:	172	AIC:	1679.
Df Residuals:	135	BIC:	1795.
Df Model:	36		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
const	-257.7503	79.904	-3.226	0.002	-415.775	-99.725
Range	-0.5074	0.516	-0.983	0.327	-1.528	0.513
A	-0.2141	1.767	-0.121	0.904	-3.708	3.280
Н	1.9158	8.275	0.232	0.817	-14.450	18.282
W	12.1233	6.723	1.803	0.074	-1.173	25.419
R	1.7515	3.250	0.539	0.591	-4.676	8.179
D	8.6807	5.300	1.638	0.104	-1.802	19.163
Move	4.7176	0.940	5.021	0.000	2.859	6.576
Wounds	3.4505	1.366	2.527	0.013	0.750	6.151
Bravery	6.3408	2.589	2.449	0.016	1.220	11.462
Save	42.4442	7.310	5.807	0.000	27.988	56.901
Ward	4.0172	6.808	0.590	0.556	-9.447	17.481
unit_size	-0.0204	2.035	-0.010	0.992	-4.044	4.004
Spells	39.1308	4.786	8.176	0.000	29.666	48.596
slaanesh_dummy	13.3755	8.542	1.566	0.120	-3.519	30.270
Wounds X model	6.6395	1.249	5.318	0.000	4.170	9.109
АХН	1.0632	5.202	0.204	0.838	-9.226	11.352
AXW	0.8068	3.761	0.215	0.830	-6.630	8.244
A_X_D	-1.2522	4.158	-0.301	0.764	-9.476	6.971
H X W	8.4850	7.496	1.132	0.260	-6.341	23.311
HXD	0.8230	7.046	0.117	0.907	-13.111	14.757
WXD	-9.3248	4.338	-2.150	0.033	-17.904	-0.746
Wounds X Save	30.6198	4.762	6.429	0.000	21.201	40.039
Wounds_X_Ward	-5.4914	5.676	-0.968	0.335	-16.716	5.733
Wounds X Bravery	-12.9485	4.342	-2.982	0.003	-21.536	-4.361
Save X Bravery	12.6823	5.519	2.298	0.023	1.768	23.597
Save X Ward	-32.3678	18.296	-1.769	0.079	-68.551	3.816
Ward X Bravery	-9.1746	8.070	-1.137	0.258	-25.134	6.785
AXHXW	5.3967	7.183	0.751	0.454	-8.809	19.602
HXWXD	7.3550	11.418	0.644	0.521	-15.226	29.936
HXAXD	-6.2425	7.235	-0.863	0.390	-20.551	8.066
Wounds X Save X Ward	10.8077	13.314	0.812	0.418	-15.524	37.139
Save X Ward X Bravery	36.8268	16.152	2.280	0.024	4.883	68.771
Save X Wounds X Bravery	27.8105	5.503	5.054	0.000	16.928	38.693
all_damage	7.9642	10.762	0.740	0.461	-13.319	29.248
all defence	7.6687	14.195	0.540	0.590	-20.405	35.743
damage X defence	0.3828	2.361	0.162	0.871	-4.287	5.053
uamage_x_derence						5.055

Negerition

Negeri



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Negative Residuals = Under-costed Units



Out[21]:		unit_name	fittedvalues	Points_per_warscroll	residuals	resid_%
	107	Chaos Spawn	117.82	70	-47.82	-68.31
	106	Raptoryx	118.38	80	-38.38	-47.98
	144	Chaos Warhounds	118.23	80	-38.23	-47.79
	100	Furies	130.88	90	-40.88	-45.42
	104	Mindstealer Sphiranx	137.24	95	-42.24	-44.46
	117	Beasts of Chaos Tzaangor Shaman	194.91	135	-59.91	-44.38
	151	Tuskgor Chariots	89.23	65	-24.23	-37.28
	155	Ungor Raiders	108.95	80	-28.95	-36.19
	24	Infernal Enrapturess	163.37	120	-43.37	-36.14
	148	Dragon Ogors	167.17	125	-42.17	-33.74
	99	Fomoroid Crusher	125.74	100	-25.74	-25.74
	143	Centigors	106.59	85	-21.59	-25.40
	122	Dragon Ogor Shaggoth	194.30	155	-39.30	-25.35
	114	Soul Grinder	283.04	230	-53.04	-23.06
	94	Chaos Warriors	268.29	220	-48.29	-21.95
	129	Ungors	79.24	65	-14.24	-21.91
	8	Syll'Esske	207.12	170	-37.12	-21.84
	97	Chaos Chosen	291.17	240	-51.17	-21.32
	54	Seeker Chariots	130.41	110	-20.41	-18.55
	150	Razorgors	64.52	55	-9.52	-17.31

Neger sample

Neger production

Neger production

Neger production

Neger production

Neger production



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Positive
Residuals =
Over-costed
Units



Out[22]:		unit_name	fittedvalues	Points_per_warscroll	residuals	resid_%
	48	Fiends	107.64	170	62.36	36.68
	39	Daemonettes	72.20	110	37.80	34.36
	96	Untamed Beasts	60.27	90	29.73	33.03
	141	Bullgors	88.68	130	41.32	31.78
	70	Chaos Lord	79.10	115	35.90	31.22
	38	Blissbarb Archers	96.35	140	43.65	31.18
	139	Bestigors	91.27	125	33.73	26.98
	127	Grashrak Fellhoof	110.71	150	39.29	26.19
	163	Chimera	151.42	200	48.58	24.29
	136	Beasts of Chaos Tzaangor Skyfires	151.75	195	43.25	22.18
	58	Seekers	101.76	130	28.24	21.72
	126	Beastlord	74.58	95	20.42	21.49
	75	Chaos Lord on Karkadrak	174.61	220	45.39	20.63
	101	Gorebeast Chariot	91.75	115	23.25	20.22
	26	Lord of Pain	103.95	130	26.05	20.04
	167	Ghorgon	128.66	155	26.34	16.99
	105	Ogroid Theridons	158.59	190	31.41	16.53
	120	Doombull	92.99	110	17.01	15.46
	93	Marauders	72.78	85	12.22	14.38
	91	Marauder Horsemen	90.34	105	14.66	13.96

Negro plane

Negro



- Uses massive computing
- Is difficult to interpret
- Tuning is timeconsuming
- Is cringe
- Algos are still being optimised
- Requires massive data

- Can literally be calculated by hand
- coefs tell you how to interpret
- What are compute costs?
- Perfected by Gauss 1795
- Requires small samples
- Is the best linear unbiased est.

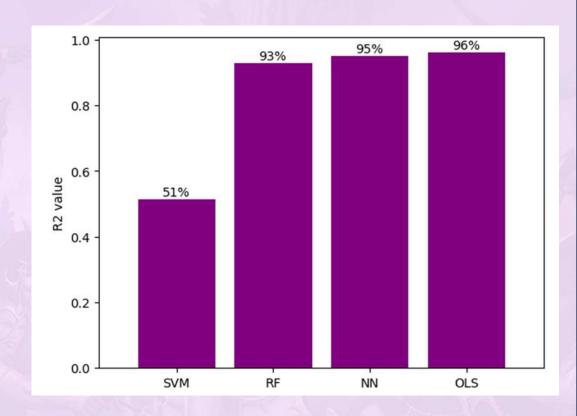
Positive
Residuals =
Over-costed
Units



ut[22]:		unit_name	fittedvalues	Points_per_warscroll	residuals	resid_%
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	91	Marauder Horsemen	90.34	105	14.66	13.96

Question:

Why did the OLS model outperform the more advanced ML approaches?





Questions:



i have never kissed a boy and at this point i'm afraid to. what if he tries to teach me about Warhammer 40k

5:16 AM · May 31, 2022

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