

Karen Ouyang



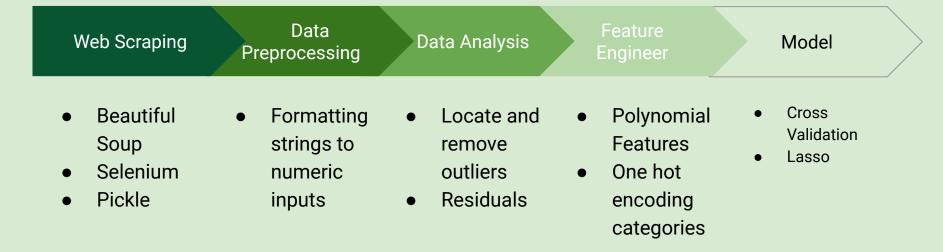
How much of your goal can you expect to receive?

- Category
- Goal Amount
- Story





Methodology





Senior Cat Rescue Marathon

Money Raised





Medica



See all

Date

Peter H. Soboroff is organizing this fundraiser.

Category

Created May 7, 2019

Animals & Pets

On June 17, I ran the Sixth Annual New York Cat Hospital SENIOR CAT RESCUE MARATHON! And as sole participant, I won...again!



Family Story

Created

ABANDONED or SURRENDERED at area shelters for being OLD, ILL, OR SIMPLY UNWANTED, countless sweet senior and special-needs cats are torn from the only homes they've known and placed in cages to await probable euthanasia.



468 1.2K 475 donors shares followers

Donate now

Social Media

Shares

Share

Anonymous

\$300 • 2 hrs

Jackie Alderman

\$50 • 18 hrs

Anonymous

\$300 • 1 d

Paula Geyh

\$50 • 1d

Edward King \$100 • 5 d



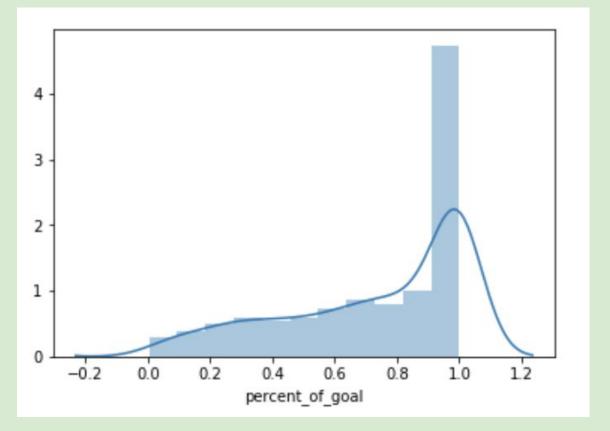
Animals



Faith

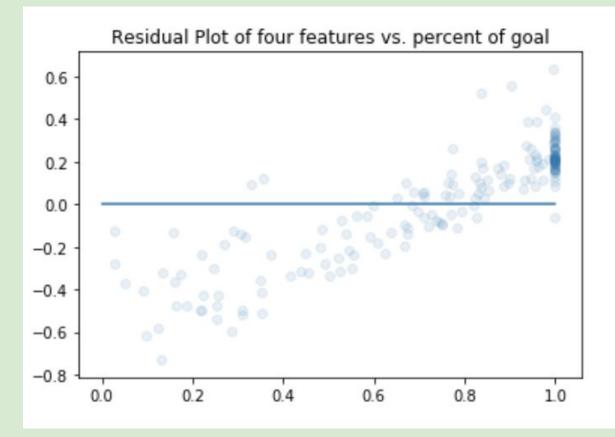


Target Distribution





Polynomial Feature Engineering might help





Multiple Linear Regression Models (941 data points)

Polynomial transformations of goal amount, word count,
 polarity and subjectivity scores (Lasso): R² = .20



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 polarity and subjectivity scores (Lasso): R² = .20

Just 18 categories dummified (Lasso): R² = 0.01

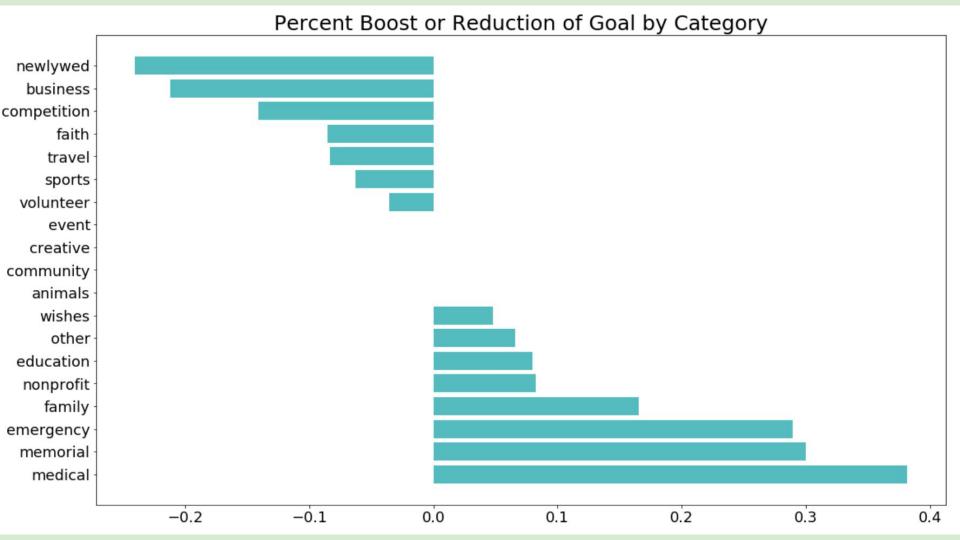


Multiple Linear Regression Models (941 data points)

Polynomial transformations of goal amount, word count,
 polarity and subjectivity scores (Lasso): R² = .20

- Just 18 categories dummified (Lasso): R² = 0.01
- Combined (Lasso): $R^2 = .43$





Conclusions

Top 3 Unpopular Categories (Reduce Predicted Percent of Goal Raised):

Newlywed, Business, Competition

Top 3 Popular Categories (Boost Predicted Percent of Goal Raised):

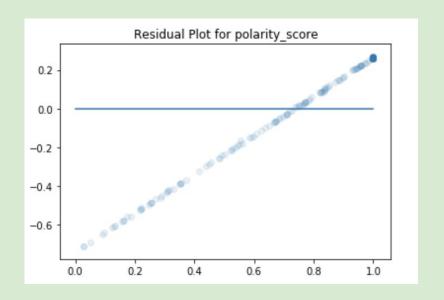
Medical, Memorial, Emergency

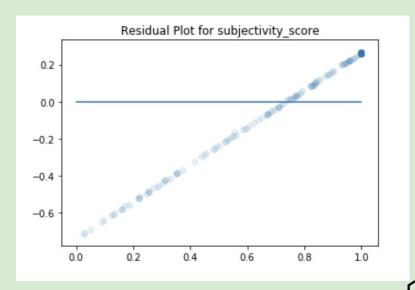
$$R^2$$
 score (Lasso) = .43

(Model has some predictive power.)



Appendix A







Appendix B

OLS Regression Results								
Dep. Variable	e: perc	ent_of_goal	ı	R-squar	ed:	0.15	58	
Mode	el:	OLS	Adj. I	R-squar	ed:	0.15	57	
Method	d: Lea	ast Squares		F-statis	tic:	178	4.1	
Date	e: Thu,	18 Jul 2019	Prob (F	-statist	ic):	2.33e-3	37	
Time	e:	14:04:42	Log-l	Likeliho	od:	-86.06	33	
No. Observations	s:	952		A	IC:	176	3.1	
Df Residual	s:	950		В	IC:	185	.8	
Df Mode	el:	1						
Covariance Type								
	coef	std err	t	P> t		0.025	0.975]	
const								
Const	0.8188	0.011	77.457	0.000		0.798	0.840	
	0.8188 518e-06		77.457 -13.345	0.000	21 - 22		_	
					21 - 22		0.840	
		1.14e-07			-1.7		0.840	
goal_clean -1.5	518e-06	1.14e-07	-13.345 Watson:	0.000	-1.7 174		0.840	
goal_clean -1.5 Omnibus:	73.693	1.14e-07 Durbin- Jarque-B	-13.345 Watson:	0.000	-1.7 174 122		0.840	

OLS Regression Results							
Dep. Variable:	perce	nt_of_goa	ı	R-sq	uared:	0.022	
Model:		OLS	S Ac	dj. R-sq	uared:	0.021	
Method:	Leas	st Squares	3	F-sta	atistic:	20.72	
Date:	Thu, 1	8 Jul 2019	Pro	b (F-sta	tistic):	6.03e-06	
Time:		13:25:22	2 Lo	g-Likel	ihood:	-152.00	
No. Observations:		941	I		AIC:	308.0	
Df Residuals:		939)		BIC:	317.7	
Df Model:			I				
Covariance Type:		nonrobus	t				
С	oef s	td err	t	P> t	[0.025	0.975]	
const 0.79			t 3.849	P> t 0.000	[0.025 0.762	0.975] 0.819	
	905	0.015 5	171		1 - A. O. 790 (10 & 10	-	
const 0.79 word_count -0.00	905	0.015 5 7e-05 -	3.849	0.000	0.762	0.819	
const 0.79 word_count -0.00	905 002 3.5	0.015 5 7e-05 -	3.849 4.551 n-Wats	0.000 0.000	0.762	0.819	
const 0.79 word_count -0.00 Omnibus:	905 002 3.5 101.653	0.015 5 7e-05 - Durbi	3.849 4.551 n-Wats	0.000 0.000 son:	0.762 -0.000 1.796	0.819	



Appendix C

OLS Regression Results							
Dep. Variabl	e: perce	nt_of_go	al	R-squ	uared:	0.000	
Mode	el:	OL	S Ac	lj. R-sqı	ıared:	-0.001	
Metho	d: Lea	st Square	es	F-sta	tistic:	0.02672	
Dat	e: Thu, 1	8 Jul 201	9 Pro l	o (F-stat	tistic):	0.870	
Tim	e:	13:26:0	5 Lo	g-Likeli	hood:	-162.25	
No. Observation	s:	94	1		AIC:	328.5	
Df Residual	s:	93	9		BIC:	338.2	
Df Mode	el:		1				
Covariance Typ	e:	nonrobus	st				
	•				F0 00F		
	coef	std err	t	P> t	[0.025	0.975]	
const	0.7406	0.015	50.652	0.000	0.712	0.769	
polarity_score	-0.0115	0.070	-0.163	0.870	-0.149	0.126	
_	444.000				4 700		
Omnibus:	111.029	Durb	in-Wats	on:	1.796		
Prob(Omnibus):	0.000	Jarque	-Bera (JB): 1	19.731		
Skew:	-0.823		Prob(JB): 1.0	00e-26		
Kurtosis:	2.414		Cond.	No.	7.66		

OLS Regression Res	ults						
Dep. Variable:	percen	t_of_goal	R	-square	ed:	0.	.009
Model:		OLS	Adj. R	-square	ed:	0.	.008
Method:	Least	Squares	F	-statist	ic:	8.	.259
Date:	Thu, 18	Jul 2019	Prob (F	-statisti	c):	0.00	415
Time:		13:29:15	Log-L	ikelihoo	d:	-158	8.14
No. Observations:		941		A	IC:	3	20.3
Df Residuals:		939		В	IC:	33	30.0
Df Model:		1					
Covariance Type:	n	onrobust					
	coef	std err	t	P> t	[0.0	025	0.975]
const	0.6432	0.035	18.615	0.000	0.5	575	0.711
subjectivity_score	0.2055	0.072	2.874	0.004	0.0	065	0.346
Omnibus:	105.242	Durbin-	-Watson:	1.8	306		
Prob(Omnibus):	0.000	Jarque-B	era (JB):	119.1	48		
Skew:	-0.831	F	Prob(JB):	1.34e	-26		
Kurtosis:	2.471	С	ond. No.	9	.33		



Appendix D

```
a = sorted(list(zip(X train.columns, lasso model.coef )), key=lambda x:(x[1]), reverse=True)
executed in 12ms, finished 17:04:02 2019-07-18
[('medical', 0.4053419307620743),
('memorial', 0.3220248395811013),
('emergency', 0.3103948793339755),
 ('family', 0.18115671509736306),
('subjectivity score sq', 0.121712777245019),
('nonprofit', 0.10337175372043461),
 ('education', 0.09372917643687535),
 ('polarity score sq', 0.08766756195621231),
 ('other', 0.08515516741341855),
('wishes', 0.05426811376053922),
 ('polarity score', 0.01728347245747426),
 ('polarity score*subjectivity score', 0.002876832390037462),
 ('word count', 1.9494874410936483e-05),
 ('goal clean*subjectivity score', 2.783554809979415e-07),
 ('goal clean sg', 7.241047849834209e-12),
 ('subjectivity score', 0.0),
 ('animals', 0.0),
 ('community', 0.0),
 ('goal clean*word count', -2.8885300286703573e-10),
 ('word count sq', -1.4712091437890873e-08),
 ('goal clean*polarity score', -2.163443742647784e-06),
 ('goal clean', -4.6806268435334145e-06),
 ('word count*subjectivity score', -0.00010646638552996634),
 ('word count*polarity score', -0.00016905022522632486),
 ('event', -0.008614321883326824),
 ('creative', -0.011097453692479492),
 ('volunteer', -0.05111899491494909),
 ('sports', -0.09201225832626436),
('faith', -0.09618460495902338),
 ('travel', -0.09987170235078825),
 ('competition', -0.1640158246042643),
 ('business', -0.22321901440607678),
 ('newlywed', -0.25958480494288333)]
```



Appendix E

5 Fold Cross Validation scores for combined features using simple linear regression, ridge regularization, and lasso regularization

Simple regression scores: [0.3574515650848509, 0.39187393007051596,

 $0.3796770254075955, \, 0.34630392817934286, \, 0.5067102950987303]$

Ridge scores: [0.3695460732306116, 0.39838596338521015, 0.3711886254455937,

0.3492615529619597, 0.5024877225398371]

Lasso scores: [0.3807339899745644, 0.4066521482353215, 0.37657345481029625,

0.3593620064465233, 0.5101509640509447]

Simple mean cv r^2: 0.396 +- 0.057

Ridge mean cv r^2: 0.398 +- 0.054

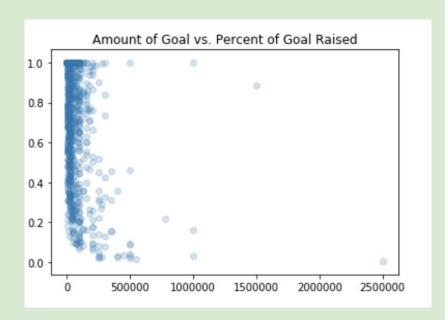
Lasso mean cv r^2: 0.407 +- 0.054

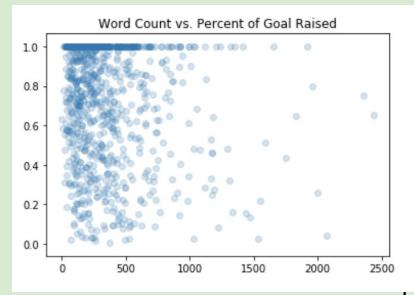


Appendix F

	goal_clean	percent_of_goal	word_count	days_active	polarity_score	subjectivity_score
count	941.000000	941.000000	941.000000	941.000000	941.000000	941.000000
mean	53583.940489	0.738747	318.285866	108.533475	0.160025	0.465167
std	74213.957804	0.287662	259.834338	234.339861	0.133964	0.130704
min	1.000000	0.019842	1.000000	1.000000	-0.500000	0.000000
25%	10000.000000	0.533200	133.000000	62.000000	0.088235	0.407762
50%	25000.000000	0.837592	244.000000	105.000000	0.151662	0.473718
75%	75000.000000	1.000000	428.000000	143.000000	0.226376	0.529816
max	500000.000000	1.000000	1468.000000	7132.000000	1.000000	1.000000

Appendix G





METIS

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morningkaren



morningkaren



Questions & Comments

