



Predicting the Competitive Tier of Pokemon

Complex Random Forest and Feature Engineering Techniques,
Giving New Tools to Gamers in the Age of Data Science

-Data Science growing in the video game industry

-Pokemon convenient for machine learning, lots of static data, turn-based, lots of untapped potential

Conclusion

The gaming industry has been growing exponentially. The number of active users tends to increase every minute and so does the overall income of the companies developing games. The inner infrastructure of the games gets even more complex providing more opportunities for players. An entirely new world and realities are created for the users. Top level visualization and design techniques, the latest visual effects, graphic elements and augmented reality effects provide customers with a high level of satisfaction.

Data science has entered various industries and improved the principles of their functioning forever. It has brought various businesses to a qualitatively new level of their development. The industry of gaming is no exception here. Moreover, data science techniques and methodologies have become integral parts of games development, design, operation, and many other stages of their functioning.

	Abomasnow			Snow Warning	Soundproof	Untiered	HP	Atk	Def	SpA	SpD	Spe	
							90	92	75	92	85	60	
	Abra			Inner Focus	Synchronize	Magic Guard	LC	HP	Atk	Def	SpA	SpD	Spe
							25	20	15	105	55	90	
	Absol			Justified	Super Luck	Pressure	PU	HP	Atk	Def	SpA	SpD	Spe
							65	130	60	75	60	75	
	Accelgor			Hydration	Unburden	Sticky Hold	Untiered	HP	Atk	Def	SpA	SpD	Spe
							80	70	40	100	60	145	
	Aegislash			Stance Change			UU	HP	Atk	Def	SpA	SpD	Spe
							60	50	140	50	140	60	
	Aegislash-Blade			Stance Change			UU	HP	Atk	Def	SpA	SpD	Spe
							60	140	50	140	50	60	
	Aerodactyl			Pressure	Unnerve	Rock Head	NU	HP	Atk	Def	SpA	SpD	Spe
							80	105	65	60	75	130	
	Aggron			Heavy Metal	Sturdy	Rock Head	PU	HP	Atk	Def	SpA	SpD	Spe
							70	110	180	60	60	50	
	Alakazam			Inner Focus	Synchronize	Magic Guard	UUBL	HP	Atk	Def	SpA	SpD	Spe
							55	50	45	135	95	120	
	Alcremie			Aroma Veil		Sweet Veil	Untiered	HP	Atk	Def	SpA	SpD	Spe
							65	60	75	110	121	64	
	Alcremie-Gmax			Aroma Veil		Sweet Veil	AG	HP	Atk	Def	SpA	SpD	Spe
							65	60	75	110	121	64	
	Altaria			Cloud Nine		Natural Cure	Untiered	HP	Atk	Def	SpA	SpD	Spe
							75	70	90	70	105	80	
	Amaura			Refrigerate		Snow Warning	LC	HP	Atk	Def	SpA	SpD	Spe
							77	59	50	67	63	46	
	Amoonguss			Effect Spore		Regenerator	UU	HP	Atk	Def	SpA	SpD	Spe
							114	85	70	85	80	30	
	Anorith			Battle Armor		Swift Swim	LC	HP	Atk	Def	SpA	SpD	Spe
							45	95	50	40	50	75	
	Appletun			Gluttony	Thick Fat	Ripen	Untiered	HP	Atk	Def	SpA	SpD	Spe
							110	85	80	100	80	30	
	Appletun-Gmax			Gluttony	Thick Fat	Ripen	AG	HP	Atk	Def	SpA	SpD	Spe
							110	85	80	100	80	30	
	Applin			Bulletproof	Ripen	Gluttony	LC	HP	Atk	Def	SpA	SpD	Spe
							40	40	80	40	40	20	
	Araquanid			Water Absorb		Water Bubble	NU	HP	Atk	Def	SpA	SpD	Spe
							68	70	92	50	132	42	
	Arcanine			Flash Fire	Justified	Intimidate	NU	HP	Atk	Def	SpA	SpD	Spe
							90	110	80	100	80	95	
	Archen			Defeatist			LC	HP	Atk	Def	SpA	SpD	Spe
							55	112	45	74	45	70	
	Archeops			Defeatist			PU	HP	Atk	Def	SpA	SpD	Spe
							75	140	65	112	65	110	
	Arctovish			Ice Body	Water Absorb	Slush Rush	NUBL	HP	Atk	Def	SpA	SpD	Spe
							90	90	100	80	90	55	

Lots of fatalistic,
and not very useful,
analysis

Lessons Learned from Analyzing Competitive Pokemon

06 Sep 2018

Ultimately, this problem ended up being unsuitable for machine learning. Essentially, the feature space was too large and the interactions between the features were too complex for a model to learn given the small training set. In other words, there are many examples of Pokemon that are in their particular tier because of some unique combination of their type, ability, moves, and stats that are quite different from other Pokemon in that tier. You can read an in depth breakdown of this in the full notebook.

Identifying Legendary Pokémon using The Random Forest Algorithm



Sylvester Cardorelle · May 31, 2019 · 7 min read



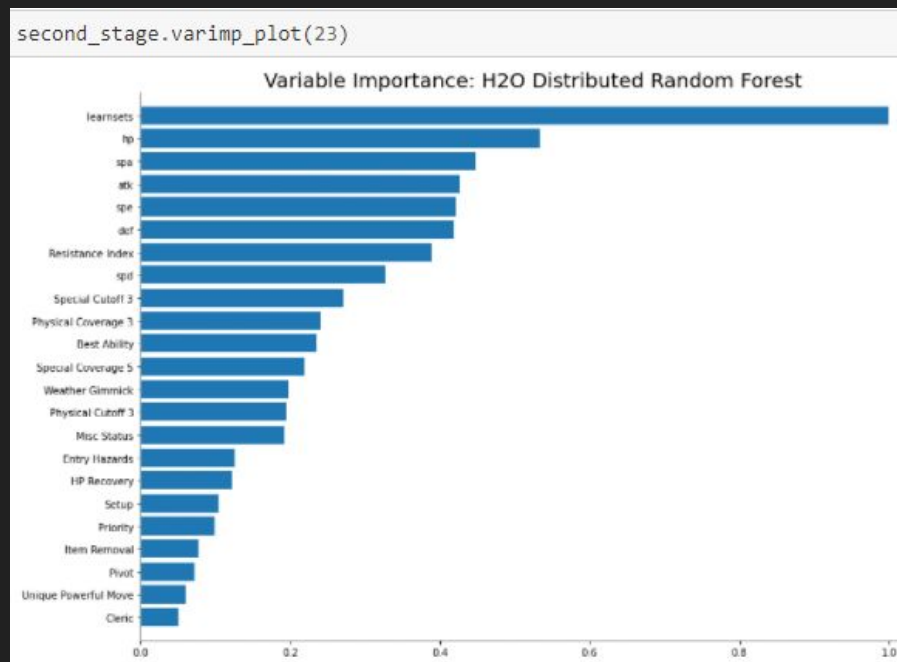
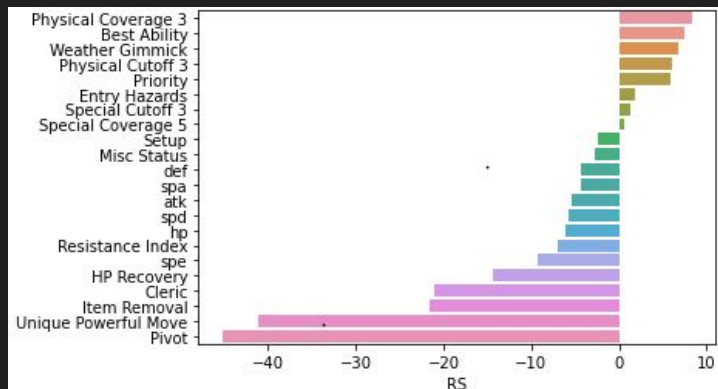
Unfortunately, there is no explicit criteria which defines these Pokémon.

The only way to identify a Legendary Pokémon is through statements from official media, such as the game or anime.

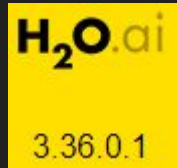
Why might an accurate model of pokemon tiers be useful?

-game design, game quality, development time, design of generations

-feature importances: recommendations for players, powering products for gamers, design of single pokemon



Results!: Scores



h2o.ai distributed random forest was best, with two stages

-training score: weighted balanced f-score is 0.887, f-scores of 7 classes range from 0.956 to 0.776

-test score: weighted balanced f-score is 0.776, f-scores of 7 classes range from 0.941 to 0.556 (and the lowest scoring classes tend to be quite small)

0.7761367825626139

Precision:

Recall:

F-Score:

Support:

```
(array([0.92105263, 0.45      , 1.          , 0.83333333, 1.          ,  
        0.86666667, 0.94117647])),  
array([0.83333333, 0.84375   , 0.54545455, 0.41666667, 0.41666667,  
        0.76470588, 0.94117647])),  
array([0.875      , 0.58695652, 0.70588235, 0.55555556, 0.58823529,  
        0.8125     , 0.94117647])),  
array([84, 32, 11, 12, 12, 17, 17], dtype=int64))
```

Benchmark Scores:

```
0.48060193774479487
```

Okay, so our classifier isn't doing great - it averages around 50% accuracy. Let's take a look into what sort of cases it's missing.

```
tiers_comp = ["LC+NFE", "Untiered+PU+NU+RU", "UU+OU+Uber+AG"]
```

```
0.7746753246753246
```

As expected, our accuracy drastically increases when we reduce the cardinality of tiers, reaching an average of around 70%. This is unfortunately still quite low. Furthermore, we haven't really improved anything, we're simply making the problem easier for the classifier.

More Benchmark Scores:

Competitive Pokemon Usage Tier Classification

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TABLE IV. PRECISION OF CLASSIFICATIONS- TEST SET WITHOUT UNDERSAMPLING

Usage Tier	Algorithm		
	J48	Lazy IBk	Logistic Regression
Ubers	.909	1.00	.900
OU	.731	1.00	.478
UUBL	.500	1.00	0.00
UU	.763	1.00	.387
RUBL	0.00	1.00	0.00
RU	.941	1.00	.438
NUBL	.500	1.00	0.00
NU	.840	1.00	.375
PU	.796	1.00	.475

TABLE I. ACCURACY OF CLASSIFICATIONS(%)

Methods	Algorithm		
	J48	Lazy IBk	Logistic Regression
Cross Validation without Undersampling	32.32	29.60	32.65
Cross Validation with Undersampling	26.00	27.00	29.50
Test Set without Undersampling	78.85	100.0	47.40
Test Set with Undersampling	64.00	78.28	47.42

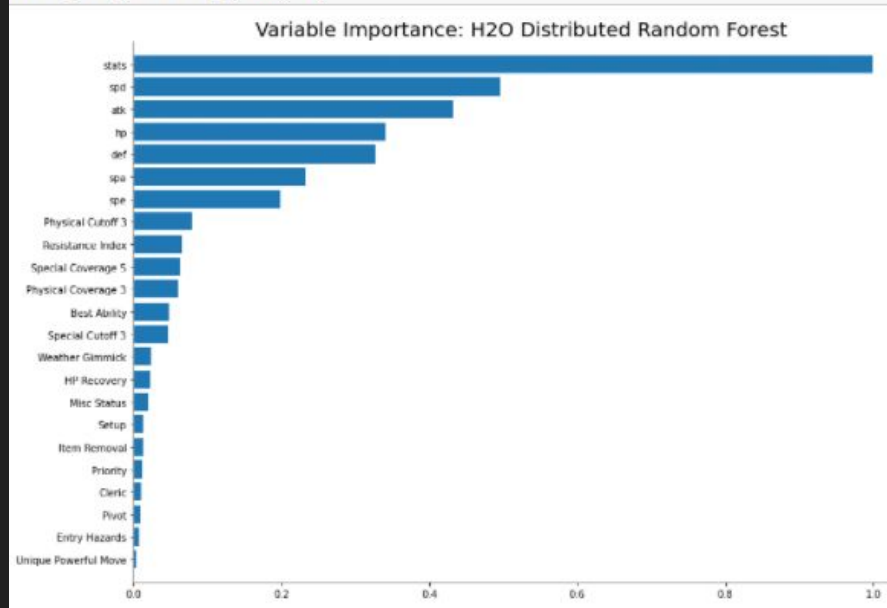
Robert Stahlbock · Gary M. Weiss
Mahmoud Abou-Nasr · Cheng-Ying Yang
Hamid R. Arabnia
Leonidas Deligiannidis *Editors*

Advances in Data Science and Information Engineering

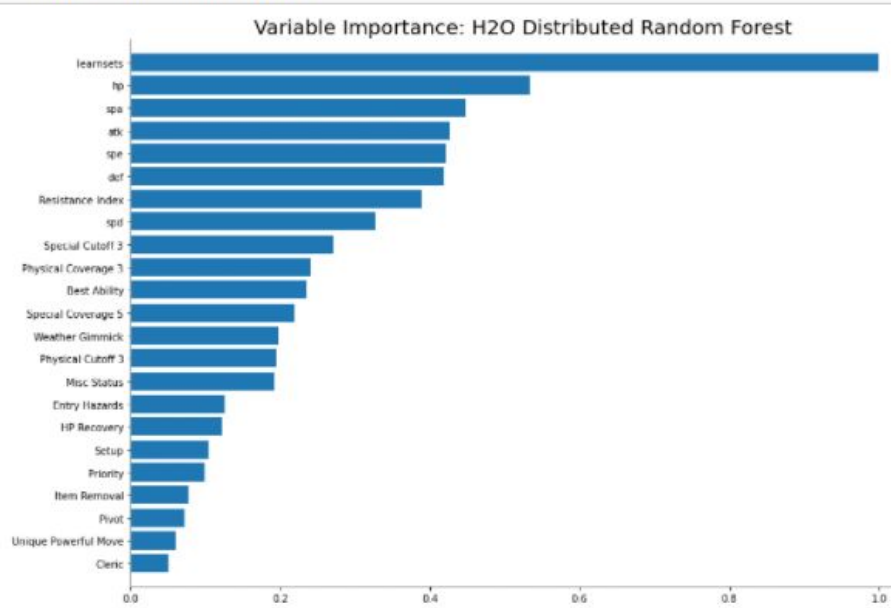
Proceedings from ICDATA 2020
and IKE 2020

More Results!: Feature Importances

```
first_stage.varimp_plot(23)
```



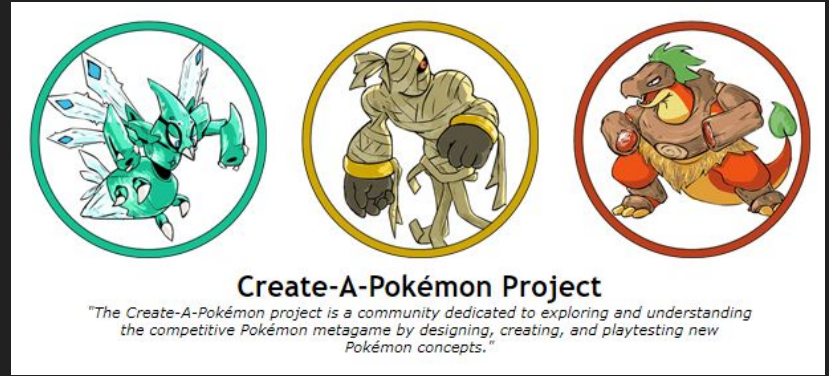
```
second_stage.varimp_plot(23)
```



What To Do With This Model?

Exactly what I mentioned earlier:

- game design, game quality, development time, design of generations
- feature importances: recommendations for players, powering products for gamers, design of single pokemon



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Approach

The 6v6 metagame

Mekkah · Oct 12, 2010

```
pokemon_df['formats'].unique()
```

```
array(['LC', 'NFE', 'RUBL', 'PU', 'NU', 'Untiered', 'UU', 'OU', 'UUBL',  
      'PUBL', 'RU', 'Uber', 'NUBL'], dtype=object)
```

```
ZU      335  
PU      153  
OU       57  
Uber     56  
RU       51  
UU       45  
NU       41  
Name: Change, dtype: int64
```



Smogon-wide Clauses

[English](#)[Español](#)[Français](#)[Italiano](#)[Português](#)

There are several clauses that apply to most official Smogon tournaments.

Species Clause

A player cannot have two Pokemon with the same species on their team.

- For example, using a team with two Koffing would be illegal.
- Using different formes on the same team, such as Koffing and Koffing Max, is also illegal (Pokedex number (#479)).

Sleep Clause

If a player has already put a Pokemon on their team to sleep, they cannot put another Pokemon on their team to sleep.

Evasion Clause

A Pokemon may not have either Double Team or Haze on its moveset.

OHKO Clause

A Pokemon may not have the moves Fissure or Guillotine on its moveset.

Moody Clause

A team cannot have a Pokemon with the ability Moody on its team.

Endless Battle Clause

Players cannot intentionally prevent an opponent from winning a battle.

Web Scraping

SCRAPING DATA FROM A JAVASCRIPT WEBPAGE WITH PYTHON

```
<!doctype html>
<html>
  <head>
    <title></title>
    <base href="/dex/">
    <link rel="stylesheet" href="media/build/dex.css.v.cuEUhCNveg-
    <script src="https://hb.vntsm.com/v3/live/ad-manager.min.js" t
    <meta name="viewport" content="width=device-width, initial-sca
    <meta name="fragment" content="!">

    <script type="text/javascript">
      dexSettings = {"injectRpcs":[[["\"dex\"","\\"dump-gens\""]
    </script>
  </head>
  <body tabindex="-1" class="theme--light">
    <div id="rich-media-placement"></div>
    <div id="container"></div>
    <div id="loading">
      <div class="spinner">
        <div class="spinner-img">Loading...</div>
      </div>
    </div>
```

Data Cleaning

<http://jsonviewer.stack.hu> :

Online JSON Viewer

JSON Viewer - Convert JSON Strings to a Friendly Readable Format.

<https://regex101.com> :

regex101: build, test, and debug regex

Regular expression tester with syntax highlighting, explanation, cheat sheet for PHP/PCRE, Python, GO, JavaScript, Java. Features a regex quiz & library.

```
strategies_dict = {}

strategydexcopy = strategydex_df.copy()

for pokemon in pokemon_df.index:
    pokemon_access = pokemon.replace("'", "").replace(
        dex_entry = strategydexcopy.loc[strategydexcopy['
    format_list = []
    for competitive_format in dex_entry['strategies']:
        format_dict = {}
        current_format = competitive_format['format']
        if current_format in acceptable_formats:
            moveset_list = []
            for moveset in competitive_format['moveset']:
                moveset_dict = {}
                moveset_name = moveset['name']
                move_list = []
                for move in moveset['moveslots']:
                    for entry in move:
                        move_list.append(entry['move'])
                moveset_dict[moveset_name] = move_list
                moveset_list.append(moveset_dict)
            format_dict[current_format] = moveset_list
            format_list.append(format_dict)
    strategies_dict[pokemon] = format_list
```

```
ed_data/PokemonData2021.csv", encoding="utf8") as infile:
```

```
.str.replace('<p>.+?</p>', '', regex=True)
.str.replace('<section>.+?</section>', '', regex=True)
.str.replace('<h1>.+?</h1>', '', regex=True)
.str.replace('\\\\\\n', '', regex=True)
.str.replace('\\', '\\')
.str.replace('King\\'s', "King's")
.str.replace('Maki\\'s', "Maki's")
.str.replace('Land\\'s', "Land's")
.str.replace('Dragon\\'s', "Dragon's")
.str.replace('Sirfetch\\'d', "Sirfetch'd")
.str.replace('Farfetch\\'d', "Farfetch'd")
.str.replace('Nature\\'s', "Nature's")
.str.replace('Forest\\'s', "Forest's")
.str.replace('drampa\\'s', "drampa's")
.str.replace('False', '\\\\')
.str.replace('True', '\\\\')
.str.replace('None', '\\\\')
.str.replace('\\\\\\\\\\\\\\\\\\'s', '\\', regex=True)
.str.replace('<ul>.+?</ul>', '', regex=True)
.str.replace('Swipe', 'False Swipe') #newline
.str.replace('Surrender', 'False Surrender') #newline
.apply(json.loads)
```


Big Problem!!!

738 rows × 14 columns

738 rows × 18 columns

738 rows × 242 columns

738 rows × 644 columns

$$14 + 18 + 242 + 644 = 918!!!$$

degrees of freedom = number of independent values – number of statistics

... models cannot be used “out of the box”, since the standard fitting algorithms all require $p < n$; in fact the usual rule of thumb is that there be **five** or ten times as many samples as variables.

Resistance Index = Resists + 2(Strong Resists) + 4(Immune) - Weaknesses - 2(Strong Weaknesses)

x		Defending type																	
		NORMAL	FIGHT	FLYING	POISON	GROUND	ROCK	BUG	GHOST	STEEL	FIRE	WATER	GRASS	ELECTR	PSYCHIC	ICE	DRAGON	DARK	FAIRY
Attacking type	NORMAL	1x	1x	1x	1x	1x	½x	1x	0x	½x	1x	1x	1x	1x	1x	1x	1x	1x	1x
	FIGHT	2x	1x	½x	½x	1x	2x	½x	0x	2x	1x	1x	1x	1x	½x	2x	1x	2x	½x
	FLYING	1x	2x	1x	1x	1x	½x	2x	1x	½x	1x	1x	2x	½x	1x	1x	1x	1x	1x
	POISON	1x	1x	1x	½x	½x	½x	1x	½x	0x	1x	1x	2x	1x	1x	1x	1x	1x	2x
	GROUND	1x	1x	0x	2x	1x	2x	½x	1x	2x	2x	1x	½x	2x	1x	1x	1x	1x	1x
	ROCK	1x	½x	2x	1x	½x	1x	2x	1x	½x	2x	1x	1x	1x	1x	2x	1x	1x	1x
	BUG	1x	½x	½x	½x	1x	1x	1x	½x	½x	½x	1x	2x	1x	2x	1x	1x	2x	½x
	GHOST	0x	1x	1x	1x	1x	1x	1x	2x	1x	1x	1x	1x	1x	2x	1x	1x	½x	1x
	STEEL	1x	1x	1x	1x	1x	2x	1x	1x	½x	½x	½x	1x	½x	1x	2x	1x	1x	2x
	FIRE	1x	1x	1x	1x	1x	½x	2x	1x	2x	½x	½x	2x	1x	1x	2x	½x	1x	1x
	WATER	1x	1x	1x	1x	2x	2x	1x	1x	1x	2x	½x	½x	1x	1x	1x	½x	1x	1x
	GRASS	1x	1x	½x	½x	2x	2x	½x	1x	½x	½x	2x	½x	1x	1x	1x	½x	1x	1x
	ELECTR	1x	1x	2x	1x	0x	1x	1x	1x	1x	1x	2x	½x	½x	1x	1x	½x	1x	1x
	PSYCHIC	1x	2x	1x	2x	1x	1x	1x	1x	½x	1x	1x	1x	1x	½x	1x	1x	0x	1x
	ICE	1x	1x	2x	1x	2x	1x	1x	1x	½x	½x	½x	2x	1x	1x	½x	2x	1x	1x
	DRAGON	1x	1x	1x	1x	1x	1x	1x	1x	½x	1x	1x	1x	1x	1x	1x	2x	1x	0x
	DARK	1x	½x	1x	1x	1x	1x	1x	2x	1x	1x	1x	1x	1x	2x	1x	1x	½x	½x
	FAIRY	1x	2x	1x	½x	1x	1x	1x	1x	½x	½x	1x	1x	1x	1x	1x	2x	2x	1x

These matchups are suitable for Generation VI onward.

Roles in Competitive Pokemon

- single out important moves and abilities
- allow for surprising niches, in spite of things like weak stats, etc.
- model could miss this easily without features

1. Utility

Entry Hazards:

Spikes: 

Stealth Rock: 

Sticky Web: 

Toxic Spikes: 

Hazard Control:

Defog: 


Magic Bounce: 

Rapid Spin: 

Clerics and Wish:

Heal Bell / Aromatherapy: 

Healing Wish: 

Lunar Dance: 

Wish: 

Other:

Knock Off (Defensive/Utility): 

Knock Off (Offensive): 

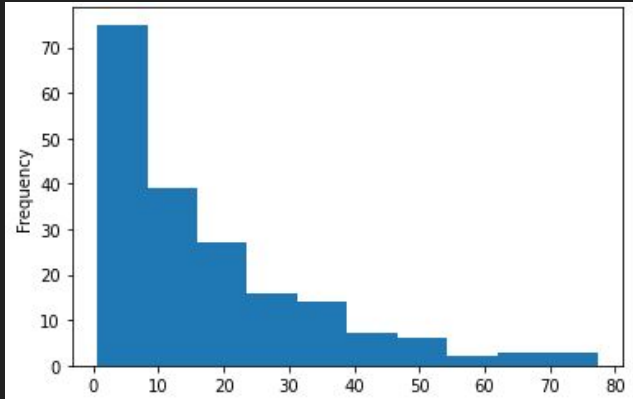
Trick: 

“C-index”: Competitiveness Index for Moves and Abilities

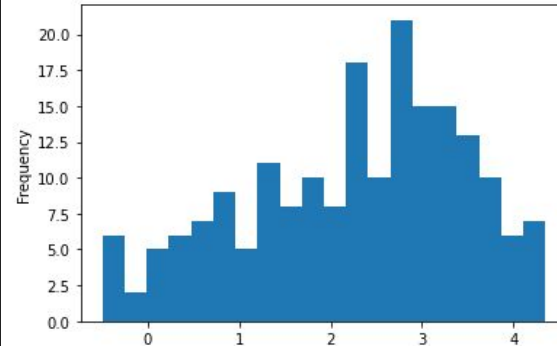
738 rows × 242 columns

738 rows × 644 columns

TF-IDF (**term frequency-inverse document frequency**) is a statistical measure that evaluates how relevant a word is to a document in a collection of documents. This is done by multiplying two metrics: how many times a word appears in a document, and the inverse document frequency of the word across a set of documents. May 10, 2019



```
index_distro_log = index_distro.apply(np.log)  
index_distro_log.plot.hist(by='cindex', bins=20)  
plt.show()
```



More About the Cindex

[Aggregate Feature: Physical Cutoff](#)
[Aggregate Feature: Physical Coverage](#)
[Aggregate Feature: Special Cutoff](#)
[Aggregate Feature: Special Coverage](#)
[Aggregate Feature: Miscellaneous Status](#)

```
sical Cutoff 5', 'Physical Cutoff 6']].corrwith(pokemon_data['format codes'])
```

```
Physical Cutoff 1    0.270197  
Physical Cutoff 2    0.284223  
Physical Cutoff 3    0.324136  
Physical Cutoff 4    0.325190  
Physical Cutoff 5    0.300717  
Physical Cutoff 6    0.276238  
dtype: float64
```

```
In [95]: n_learnset[np.abs(stats.zscore(n_learnset)) > 3]
```

```
Out[95]: 1.0    77  
        2.0    28  
        Name: n_learnset, dtype: int64
```

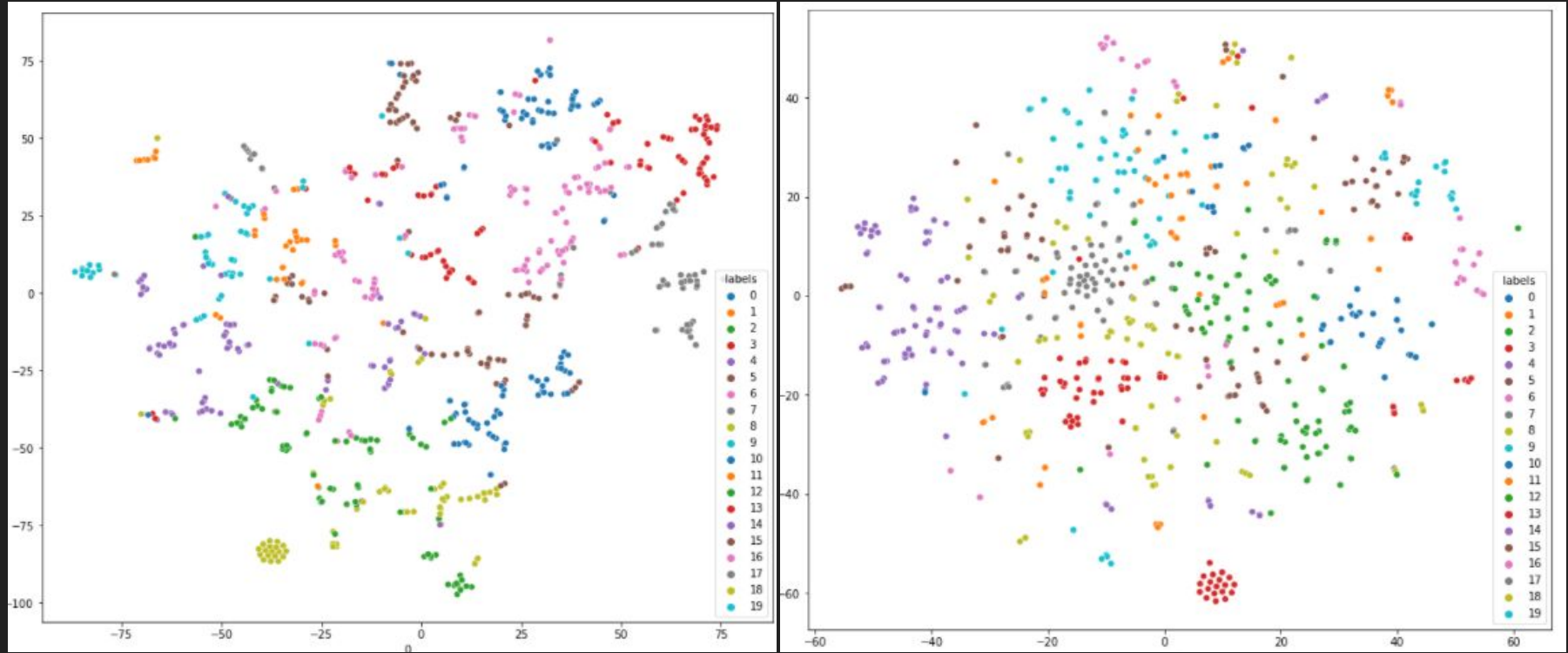
```
In [96]: n_learnset[np.abs(stats.zscore(n_learnset)) > 2]
```

```
Out[96]: 1.0    77  
        2.0    28  
        Name: n_learnset, dtype: int64
```

Unique Powerful Moves Feature

Now we need to make a feature indicating which moves with cindex 100 and n_learnset 1 or 2

Clusters: Shrinking the Decision Space



Models We Tried

- Logistic Regression, Decision Tree: Far lower accuracy on the train and test sets
- KNN: performed almost as well as Random Forest (similar to clustering)
- KNN only gives predictions, not feature importances or coefficients

Are categorical variables getting lost in your random forests?

🕒 less than 1 minute read

I've been one-hot encoding categorical variables for as long as I have been using sci-kit learn. It turns out that you can lose a lot of predictive power this way, and that alternatives do exist.

Decision tree models can handle categorical variables without one-hot encoding them. However, popular implementations of decision trees (and random forests) differ as to whether they honor this fact. We show that one-hot encoding can seriously degrade tree-model performance. Our primary comparison is between H2O (which honors categorical variables) and scikit-learn (which requires them to be one-hot encoded).

Distributed Random Forest (DRF)

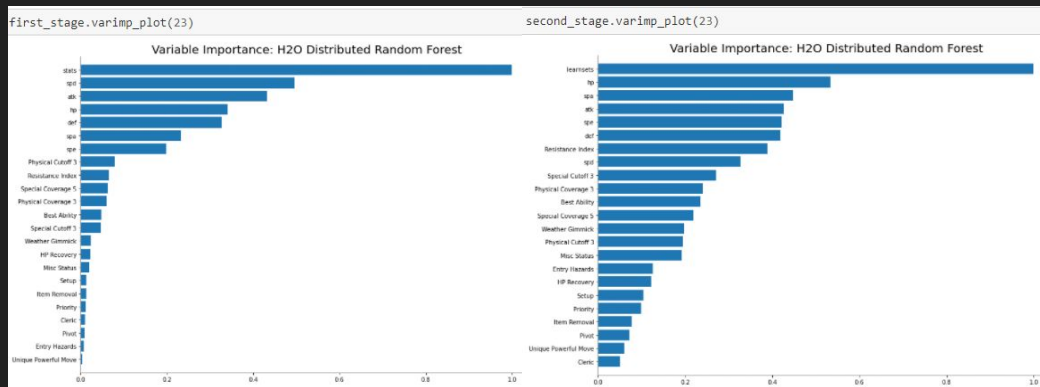
Our most important feature (proven by feature importances) was clustering, which is categorical, so it may have been essential that h2o could properly assign importance to it!

Improved ability to train on categorical variables (using the `nbins_cats` parameter)

Two-Stage Modeling!

significantly improved accuracy, and especially helped with overfitting

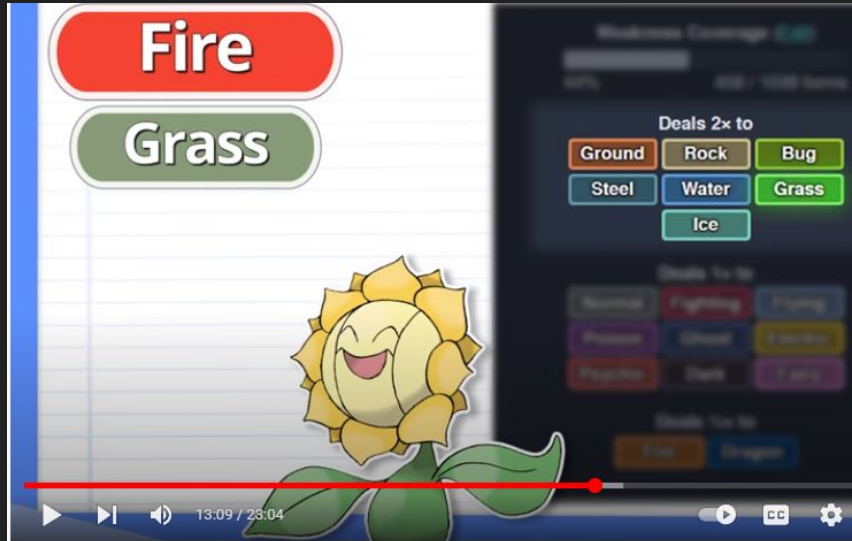
```
ZU      335
PU      153
OU       57
Uber     56
RU       51
UU       45
NU       41
Name: Change, dtype: int64
```



-model for the higher 6 classes has more balanced feature importances

-also tried three-stage, due to size of PU, but this did not improve accuracy on training or test data

Future Ideas!



#PokemonSwordShield #WolfeyVGC #Pokemon

Every Type Combination That Doesn't Exist RANKED

