Session_5_Project_Aloagbaye

November 9, 2018

0.1 Pokemon DB :

Download the "pokedex.sqlite" db from : https://www.dropbox.com/s/dhcz0ryqoxeqqrf/pokedex.sqlite?dl=0
Try to explore and see what is in the DB:

```
In [1]: import sqlite3
        con = sqlite3.connect("./pokedex.sqlite")
        cur=con.cursor()

In [2]: # Use this command below to see the list of tables in the DB
        cur.execute("SELECT name FROM sqlite_master WHERE type='table';")
        all_tables=cur.fetchall()
```

0.1.1 Types :

```
In [3]: # Write a query to output the type_id, name for different type of Pokemon and only whe
        cur.execute("SELECT type_id, name FROM 'type_names' WHERE local_language_id=9;")
        cur.fetchall()

Out[3]: [(1, 'Normal'),
         (2, 'Fighting'),
         (3, 'Flying'),
         (4, 'Poison'),
         (5, 'Ground'),
         (6, 'Rock'),
         (7, 'Bug'),
         (8, 'Ghost'),
         (9, 'Steel'),
         (10, 'Fire'),
         (11, 'Water'),
         (12, 'Grass'),
         (13, 'Electric'),
         (14, 'Psychic'),
         (15, 'Ice'),
         (16, 'Dragon'),
         (17, 'Dark'),
         (10001, '???'),
         (10002, 'Shadow')]
```

0.1.2 Gen 1 moves :

```
In [65]: # Write a query to output the name of the move and name of the type for Generation 1 m
         #You wanna look into move_names,moves and type_names tables

         #You should see an output like this :
```

```
Out[65]: [(u'Pound', u'Normal'),
          (u'DoubleSlap', u'Normal'),
          (u'Comet Punch', u'Normal'),
          (u'Mega Punch', u'Normal'),
          (u'Pay Day', u'Normal'),
          (u'Scratch', u'Normal'),
          (u'ViceGrip', u'Normal'),
          (u'Guillotine', u'Normal'),
          (u'Razor Wind', u'Normal'),
          (u'Swords Dance', u'Normal'),
          (u'Cut', u'Normal'),
          (u'Whirlwind', u'Normal'),
          (u'Bind', u'Normal'),
          (u'Slam', u'Normal'),
          (u'Stomp', u'Normal'),
          (u'Mega Kick', u'Normal'),
          (u'Headbutt', u'Normal'),
          (u'Horn Attack', u'Normal'),
          (u'Fury Attack', u'Normal'),
          (u'Horn Drill', u'Normal'),
          (u'Tackle', u'Normal'),
          (u'Body Slam', u'Normal'),
          (u'Wrap', u'Normal'),
          (u'Take Down', u'Normal'),
          (u'Thrash', u'Normal'),
          (u'Double-Edge', u'Normal'),
          (u'Tail Whip', u'Normal'),
          (u'Leer', u'Normal'),
          (u'Growl', u'Normal'),
          (u'Roar', u'Normal'),
          (u'Sing', u'Normal'),
          (u'Supersonic', u'Normal'),
          (u'SonicBoom', u'Normal'),
          (u'Disable', u'Normal'),
          (u'Hyper Beam', u'Normal'),
          (u'Strength', u'Normal'),
          (u'Growth', u'Normal'),
          (u'Quick Attack', u'Normal'),
          (u'Rage', u'Normal'),
          (u'Mimic', u'Normal'),
          (u'Screech', u'Normal'),
          (u'Double Team', u'Normal'),
```

```
(u'Recover', u'Normal'),
(u'Harden', u'Normal'),
(u'Minimize', u'Normal'),
(u'SmokeScreen', u'Normal'),
(u'Defense Curl', u'Normal'),
(u'Focus Energy', u'Normal'),
(u'Bide', u'Normal'),
(u'Metronome', u'Normal'),
(u'Selfdestruct', u'Normal'),
(u'Egg Bomb', u'Normal'),
(u'Swift', u'Normal'),
(u'Skull Bash', u'Normal'),
(u'Spike Cannon', u'Normal'),
(u'Constrict', u'Normal'),
(u'Softboiled', u'Normal'),
(u'Glare', u'Normal'),
(u'Barrage', u'Normal'),
(u'Lovely Kiss', u'Normal'),
(u'Transform', u'Normal'),
(u'Dizzy Punch', u'Normal'),
(u'Flash', u'Normal'),
(u'Splash', u'Normal'),
(u'Explosion', u'Normal'),
(u'Fury Swipes', u'Normal'),
(u'Hyper Fang', u'Normal'),
(u'Sharpen', u'Normal'),
(u'Conversion', u'Normal'),
(u'Tri Attack', u'Normal'),
(u'Super Fang', u'Normal'),
(u'Slash', u'Normal'),
(u'Substitute', u'Normal'),
(u'Struggle', u'Normal'),
(u'Karate Chop', u'Fighting'),
(u'Double Kick', u'Fighting'),
(u'Jump Kick', u'Fighting'),
(u'Rolling Kick', u'Fighting'),
(u'Submission', u'Fighting'),
(u'Low Kick', u'Fighting'),
(u'Counter', u'Fighting'),
(u'Seismic Toss', u'Fighting'),
(u'Hi Jump Kick', u'Fighting'),
(u'Gust', u'Flying'),
(u'Wing Attack', u'Flying'),
(u'Fly', u'Flying'),
(u'Peck', u'Flying'),
(u'Drill Peck', u'Flying'),
(u'Mirror Move', u'Flying'),
(u'Sky Attack', u'Flying'),
```

```
(u'Poison Sting', u'Poison'),
(u'Acid', u'Poison'),
(u'PoisonPowder', u'Poison'),
(u'Toxic', u'Poison'),
(u'Smog', u'Poison'),
(u'Sludge', u'Poison'),
(u'Poison Gas', u'Poison'),
(u'Acid Armor', u'Poison'),
(u'Sand-Attack', u'Ground'),
(u'Earthquake', u'Ground'),
(u'Fissure', u'Ground'),
(u'Dig', u'Ground'),
(u'Bone Club', u'Ground'),
(u'Bonemerang', u'Ground'),
(u'Rock Throw', u'Rock'),
(u'Rock Slide', u'Rock'),
(u'Twineedle', u'Bug'),
(u'Pin Missile', u'Bug'),
(u'String Shot', u'Bug'),
(u'Leech Life', u'Bug'),
(u'Night Shade', u'Ghost'),
(u'Confuse Ray', u'Ghost'),
(u'Lick', u'Ghost'),
(u'Fire Punch', u'Fire'),
(u'Ember', u'Fire'),
(u'Flamethrower', u'Fire'),
(u'Fire Spin', u'Fire'),
(u'Fire Blast', u'Fire'),
(u'Water Gun', u'Water'),
(u'Hydro Pump', u'Water'),
(u'Surf', u'Water'),
(u'BubbleBeam', u'Water'),
(u'Withdraw', u'Water'),
(u'Waterfall', u'Water'),
(u'Clamp', u'Water'),
(u'Bubble', u'Water'),
(u'Crabhammer', u'Water'),
(u'Vine Whip', u'Grass'),
(u'Absorb', u'Grass'),
(u'Mega Drain', u'Grass'),
(u'Leech Seed', u'Grass'),
(u'Razor Leaf', u'Grass'),
(u'SolarBeam', u'Grass'),
(u'Stun Spore', u'Grass'),
(u'Sleep Powder', u'Grass'),
(u'Petal Dance', u'Grass'),
(u'Spore', u'Grass'),
(u'ThunderPunch', u'Electric'),
```

```
 (u'ThunderShock', u'Electric'),
 (u'Thunderbolt', u'Electric'),
 (u'Thunder Wave', u'Electric'),
 (u'Thunder', u'Electric'),
 (u'Psybeam', u'Psychic'),
 (u'Confusion', u'Psychic'),
 (u'Psychic', u'Psychic'),
 (u'Hypnosis', u'Psychic'),
 (u'Meditate', u'Psychic'),
 (u'Agility', u'Psychic'),
 (u'Teleport', u'Psychic'),
 (u'Barrier', u'Psychic'),
 (u'Light Screen', u'Psychic'),
 (u'Reflect', u'Psychic'),
 (u'Amnesia', u'Psychic'),
 (u'Kinesis', u'Psychic'),
 (u'Dream Eater', u'Psychic'),
 (u'Psywave', u'Psychic'),
 (u'Rest', u'Psychic'),
 (u'Ice Punch', u'Ice'),
 (u'Mist', u'Ice'),
 (u'Ice Beam', u'Ice'),
 (u'Blizzard', u'Ice'),
 (u'Aurora Beam', u'Ice'),
 (u'Haze', u'Ice'),
 (u'Dragon Rage', u'Dragon'),
 (u'Bite', u'Dark')]
```

0.1.3 It is hard to write custome queries each time. Lets use the power of Pandas/Python by getting everything into Pandas DF:

```
In [4]: # Use "for loops" to read each table in the DB and store it as a df with the same name
        cur.execute("SELECT identifier, type_names.name FROM 'moves' JOIN 'type_names' ON moves
        cur.fetchall()
```

```
Out[4]: [('twineedle', 'Bug'),
         ('pin-missile', 'Bug'),
         ('string-shot', 'Bug'),
         ('leech-life', 'Bug'),
         ('bite', 'Dark'),
         ('dragon-rage', 'Dragon'),
         ('thunderpunch', 'Electric'),
         ('thundershock', 'Electric'),
         ('thunderbolt', 'Electric'),
         ('thunder-wave', 'Electric'),
         ('thunder', 'Electric'),
         ('karate-chop', 'Fighting'),
         ('double-kick', 'Fighting'),
```

```
('jump-kick', 'Fighting'),
('rolling-kick', 'Fighting'),
('submission', 'Fighting'),
('low-kick', 'Fighting'),
('counter', 'Fighting'),
('seismic-toss', 'Fighting'),
('hi-jump-kick', 'Fighting'),
('fire-punch', 'Fire'),
('ember', 'Fire'),
('flamethrower', 'Fire'),
('fire-spin', 'Fire'),
('fire-blast', 'Fire'),
('gust', 'Flying'),
('wing-attack', 'Flying'),
('fly', 'Flying'),
('peck', 'Flying'),
('drill-peck', 'Flying'),
('mirror-move', 'Flying'),
('sky-attack', 'Flying'),
('night-shade', 'Ghost'),
('confuse-ray', 'Ghost'),
('lick', 'Ghost'),
('vine-whip', 'Grass'),
('absorb', 'Grass'),
('mega-drain', 'Grass'),
('leech-seed', 'Grass'),
('razor-leaf', 'Grass'),
('solarbeam', 'Grass'),
('stun-spore', 'Grass'),
('sleep-powder', 'Grass'),
('petal-dance', 'Grass'),
('spore', 'Grass'),
('sand-attack', 'Ground'),
('earthquake', 'Ground'),
('fissure', 'Ground'),
('dig', 'Ground'),
('bone-club', 'Ground'),
('bonemerang', 'Ground'),
('ice-punch', 'Ice'),
('mist', 'Ice'),
('ice-beam', 'Ice'),
('blizzard', 'Ice'),
('aurora-beam', 'Ice'),
('haze', 'Ice'),
('pound', 'Normal'),
('doubleslap', 'Normal'),
('comet-punch', 'Normal'),
('mega-punch', 'Normal'),
```

```
('pay-day', 'Normal'),
('scratch', 'Normal'),
('vicegrip', 'Normal'),
('guillotine', 'Normal'),
('razor-wind', 'Normal'),
('swords-dance', 'Normal'),
('cut', 'Normal'),
('whirlwind', 'Normal'),
('bind', 'Normal'),
('slam', 'Normal'),
('stomp', 'Normal'),
('mega-kick', 'Normal'),
('headbutt', 'Normal'),
('horn-attack', 'Normal'),
('fury-attack', 'Normal'),
('horn-drill', 'Normal'),
('tackle', 'Normal'),
('body-slam', 'Normal'),
('wrap', 'Normal'),
('take-down', 'Normal'),
('thrash', 'Normal'),
('double-edge', 'Normal'),
('tail-whip', 'Normal'),
('leer', 'Normal'),
('growl', 'Normal'),
('roar', 'Normal'),
('sing', 'Normal'),
('supersonic', 'Normal'),
('sonicboom', 'Normal'),
('disable', 'Normal'),
('hyper-beam', 'Normal'),
('strength', 'Normal'),
('growth', 'Normal'),
('quick-attack', 'Normal'),
('rage', 'Normal'),
('mimic', 'Normal'),
('screech', 'Normal'),
('double-team', 'Normal'),
('recover', 'Normal'),
('harden', 'Normal'),
('minimize', 'Normal'),
('smokescreen', 'Normal'),
('defense-curl', 'Normal'),
('focus-energy', 'Normal'),
('bide', 'Normal'),
('metronome', 'Normal'),
('selfdestruct', 'Normal'),
('egg-bomb', 'Normal'),
```

```
('swift', 'Normal'),
('skull-bash', 'Normal'),
('spike-cannon', 'Normal'),
('constrict', 'Normal'),
('softboiled', 'Normal'),
('glare', 'Normal'),
('barrage', 'Normal'),
('lovely-kiss', 'Normal'),
('transform', 'Normal'),
('dizzy-punch', 'Normal'),
('flash', 'Normal'),
('splash', 'Normal'),
('explosion', 'Normal'),
('fury-swipes', 'Normal'),
('hyper-fang', 'Normal'),
('sharpen', 'Normal'),
('conversion', 'Normal'),
('tri-attack', 'Normal'),
('super-fang', 'Normal'),
('slash', 'Normal'),
('substitute', 'Normal'),
('struggle', 'Normal'),
('poison-sting', 'Poison'),
('acid', 'Poison'),
('poisonpowder', 'Poison'),
('toxic', 'Poison'),
('smog', 'Poison'),
('sludge', 'Poison'),
('poison-gas', 'Poison'),
('acid-armor', 'Poison'),
('psybeam', 'Psychic'),
('confusion', 'Psychic'),
('psychic', 'Psychic'),
('hypnosis', 'Psychic'),
('meditate', 'Psychic'),
('agility', 'Psychic'),
('teleport', 'Psychic'),
('barrier', 'Psychic'),
('light-screen', 'Psychic'),
('reflect', 'Psychic'),
('amnesia', 'Psychic'),
('kinesis', 'Psychic'),
('dream-eater', 'Psychic'),
('psywave', 'Psychic'),
('rest', 'Psychic'),
('rock-throw', 'Rock'),
('rock-slide', 'Rock'),
('water-gun', 'Water'),
```

```
 ('hydro-pump', 'Water'),
 ('surf', 'Water'),
 ('bubblebeam', 'Water'),
 ('withdraw', 'Water'),
 ('waterfall', 'Water'),
 ('clamp', 'Water'),
 ('bubble', 'Water'),
 ('crabhammer', 'Water')]
```

0.2 back to Pandas, some data exploration :

Download another Pokemon dataset from here :https://www.dropbox.com/s/ms0tixxeflq1toc/Pokemon.csv?dl
Lets explore:

```
In [6]: # Use "for loops" to read each table in the DB and store it as a df with the same name
        import pandas as pd
        table_headers =[]
        for table in all_tables:
            table =table[0]
            name = table+"_df"
            query = "SELECT * FROM "+ table
            vars()[name] = pd.read_sql(query,con)
            print(name)
            #df.to_excel(table+'.xlsx')
```

```
conquest_move_displacements_df
encounter_methods_df
move_targets_df
berry_firmness_df
pokemon_move_methods_df
conquest_warrior_stats_df
item_flags_df
item_fling_effects_df
item_pockets_df
move_damage_classes_df
evolution_triggers_df
contest_effects_df
pokemon_habitats_df
genders_df
super_contest_effects_df
conquest_move_ranges_df
move_meta_categories_df
egg_groups_df
conquest_episodes_df
contest_types_df
move_flags_df
conquest_warrior_archetypes_df
conquest_stats_df
```

```
encounter_conditions_df
pokemon_colors_df
move_battle_styles_df
pal_park_areas_df
move_effects_df
regions_df
conquest_move_effects_df
growth_rates_df
languages_df
pokeathlon_stats_df
conquest_warrior_skills_df
pokemon_shapes_df
move_meta_ailments_df
stats_df
conquest_warrior_skill_names_df
conquest_move_displacement_prose_df
pokemon_color_names_df
encounter_condition_prose_df
item_fling_effect_prose_df
pokedexes_df
evolution_trigger_prose_df
experience_df
berry_firmness_names_df
move_meta_ailment_names_df
move_effect_prose_df
growth_rate_prose_df
conquest_stat_names_df
move_flag_prose_df
item_pocket_names_df
encounter_method_prose_df
region_names_df
item_flag_prose_df
move_target_prose_df
pokemon_move_method_prose_df
pokeathlon_stat_names_df
conquest_move_range_prose_df
pokemon_shape_prose_df
item_categories_df
pokemon_habitat_names_df
contest_effect_prose_df
encounter_condition_values_df
move_damage_class_prose_df
locations_df
super_contest_effect_prose_df
language_names_df
pal_park_area_names_df
conquest_episode_names_df
contest_type_names_df
```

```
move_meta_category_prose_df
conquest_warrior_stat_names_df
conquest_warriors_df
move_battle_style_prose_df
egg_group_prose_df
conquest_move_effect_prose_df
natures_df
stat_names_df
pokedex_prose_df
stat_hints_df
conquest_episode_warriors_df
generations_df
conquest_warrior_names_df
encounter_condition_value_prose_df
location_names_df
items_df
conquest_warrior_ranks_df
item_category_prose_df
location_areas_df
nature_battle_style_preferences_df
generation_names_df
item_game_indices_df
conquest_warrior_rank_stat_map_df
item_flag_map_df
version_groups_df
location_area_prose_df
item_flavor_summaries_df
item_prose_df
evolution_chains_df
nature_pokeathlon_stats_df
item_names_df
nature_names_df
types_df
stat_hint_names_df
abilities_df
location_game_indices_df
move_effect_changelog_df
versions_df
pokemon_species_df
version_group_regions_df
type_efficacy_df
ability_prose_df
version_group_pokemon_move_methods_df
ability_flavor_text_df
berries_df
conquest_warrior_specialties_df
encounter_slots_df
conquest_kingdoms_df
```

```
ability_names_df
moves_df
conquest_warrior_transformation_df
type_names_df
ability_changelog_df
item_flavor_text_df
pokemon_species_flavor_text_df
pokemon_egg_groups_df
pokemon_df
conquest_transformation_warriors_df
move_changelog_df
conquest_kingdom_names_df
conquest_pokemon_abilities_df
move_flavor_text_df
pal_park_df
super_contest_combos_df
move_meta_stat_changes_df
pokemon_evolution_df
version_names_df
contest_combos_df
conquest_pokemon_moves_df
machines_df
move_effect_changelog_prose_df
pokemon_dex_numbers_df
pokemon_species_flavor_summaries_df
berry_flavors_df
pokemon_species_prose_df
conquest_pokemon_evolution_df
conquest_max_links_df
conquest_transformation_pokemon_df
location_area_encounter_rates_df
move_meta_df
conquest_move_data_df
move_flavor_summaries_df
move_names_df
ability_changelog_prose_df
pokemon_species_names_df
conquest_pokemon_stats_df
move_flag_map_df
pokemon_abilities_df
encounters_df
pokemon_stats_df
pokemon_items_df
pokemon_game_indices_df
pokemon_types_df
pokemon_moves_df
pokemon_forms_df
pokemon_form_names_df
```

```
pokemon_form_generations_df
encounter_condition_value_map_df
pokemon_form_pokeathlon_stats_df
```

In [7]:
```
#Let's rename the # column to id, and convert all column labels to lower case.
# use df.rename to rename the # column to id
# use df.columns.str.lower() to convert all column labels to lower case
df = pd.read_csv('Pokemon.csv')
df.head()
```

Out[7]:

	#	Name	Type 1	Type 2	Total	HP	Attack	Defense	Sp. Atk	Sp. Def	Speed	Generation	Legendary
0	1	Bulbasaur	Grass	Poison	318	45	49	49	65	65	45	1	False
1	2	Ivysaur	Grass	Poison	405	60	62	63	80	80	60	1	False
2	3	Venusaur	Grass	Poison	525	80	82	83	100	100	80	1	False
3	3	VenusaurMega Venusaur	Grass	Poison	625	80	100	123	122	120	80	1	False
4	4	Charmander	Fire	NaN	309	39	52	43	60	50	65	1	False

In [8]:
```
#Let's rename the # column to id, and convert all column labels to lower case.
# use df.rename to rename the # column to id
df = df.rename(columns={'#': 'id'})
# use df.columns.str.lower() to convert all column labels to lower case
df.columns = df.columns.str.lower()
# you should see:
df.head()
```

Out[8]:

	id	name	type 1	type 2	total	hp	attack	defense	sp. atk	sp. def	speed	generation	legendary
0	1	Bulbasaur	Grass	Poison	318	45	49	49	65	65	45	1	False
1	2	Ivysaur	Grass	Poison	405	60	62	63	80	80	60	1	False
2	3	Venusaur	Grass	Poison	525	80	82	83	100	100	80	1	False
3	3	VenusaurMega Venusaur	Grass	Poison	625	80	100	123	122	120	80	1	False
4	4	Charmander	Fire	NaN	309	39	52	43	60	50	65	1	False

In [9]:
```
# Lets exclude these duplicates in our analysis except for the first instance.
df = df.drop_duplicates(['id'],keep='first')
```

```
df[df.duplicated('id', keep=False)].head()
# use df.drop_duplicates
```

Out[9]:
```
Empty DataFrame
Columns: [id, name, type 1, type 2, total, hp, attack, defense, sp. atk, sp. def, speed
Index: []
```

In [10]:
```
import numpy as np
df['type 2']
```

Out[10]:
```
0      Poison
1      Poison
2      Poison
4         NaN
5         NaN
6      Flying
9         NaN
10        NaN
11        NaN
13        NaN
14        NaN
15     Flying
16     Poison
17     Poison
18     Poison
20     Flying
21     Flying
22     Flying
24        NaN
25        NaN
26     Flying
27     Flying
28        NaN
29        NaN
30        NaN
31        NaN
32        NaN
33        NaN
34        NaN
35        NaN
         ...
762       NaN
763       NaN
764    Normal
765    Normal
766    Dragon
767    Dragon
768       Ice
```

```
769       Ice
770       NaN
771    Flying
772     Fairy
773     Fairy
774       NaN
775       NaN
776       NaN
777     Fairy
778     Grass
779     Grass
780     Grass
784     Grass
788       NaN
789       NaN
790    Dragon
791    Dragon
792       NaN
793    Flying
794    Ground
795     Fairy
797     Ghost
799     Water
Name: type 2, Length: 721, dtype: object
```

In [28]:
```
# Fill the Nan values
df['type 2']=df['type 2'].fillna("None")
```

In [29]:
```
#The dataset contains both information regarding the identity and statistics of each
#let's separate these two observational units into separate tables: pokedex and stati
# create pokedex with these columns: ['id', 'name', 'type 1', 'type 2', 'generation',
pokedex = df[['id', 'name', 'type 1', 'type 2', 'generation', 'legendary']]
pokedex.head()
```

Out[29]:

	id	name	type 1	type 2	generation	legendary
0	1	Bulbasaur	Grass	Poison	1	False
1	2	Ivysaur	Grass	Poison	1	False
2	3	Venusaur	Grass	Poison	1	False
4	4	Charmander	Fire	None	1	False
5	5	Charmeleon	Fire	None	1	False

In [75]:
```
# create poke_statistics with these columns:['id', 'hp', 'attack', 'defense', 'sp. at
poke_statistics = df[['id', 'hp', 'attack', 'defense', 'sp. atk', 'sp. def', 'speed',
poke_statistics.head()
```

Out[75]:

	id	hp	attack	defense	sp. atk	sp. def	speed	total
0	1	45	49	49	65	65	45	318
1	2	60	62	63	80	80	60	405
2	3	80	82	83	100	100	80	525

```
4   4  39      52       43       60       50      65     309
5   5  58      64       58       80       65      80     405
```

```
In [31]: poke_statistics.describe()
```

```
Out[31]:              id          hp      attack     defense     sp. atk     sp. def  \
count  721.00000  721.000000  721.000000  721.000000  721.000000  721.000000
mean   361.00000   68.380028   75.124827   70.697642   68.848821   69.180305
std    208.27906   25.848272   29.070335   29.194941   28.898590   26.899364
min      1.00000    1.000000    5.000000    5.000000   10.000000   20.000000
25%    181.00000   50.000000   54.000000   50.000000   45.000000   50.000000
50%    361.00000   65.000000   75.000000   65.000000   65.000000   65.000000
75%    541.00000   80.000000   95.000000   85.000000   90.000000   85.000000
max    721.00000  255.000000  165.000000  230.000000  154.000000  230.000000

              speed       total
count  721.000000  721.000000
mean    65.714286  417.945908
std     27.277920  109.663671
min      5.000000  180.000000
25%     45.000000  320.000000
50%     65.000000  424.000000
75%     85.000000  499.000000
max    160.000000  720.000000
```

0.2.1 Now we have a clean dataset.

0.2.2 Lets see : How are Pokemon numbers distributed across generations?

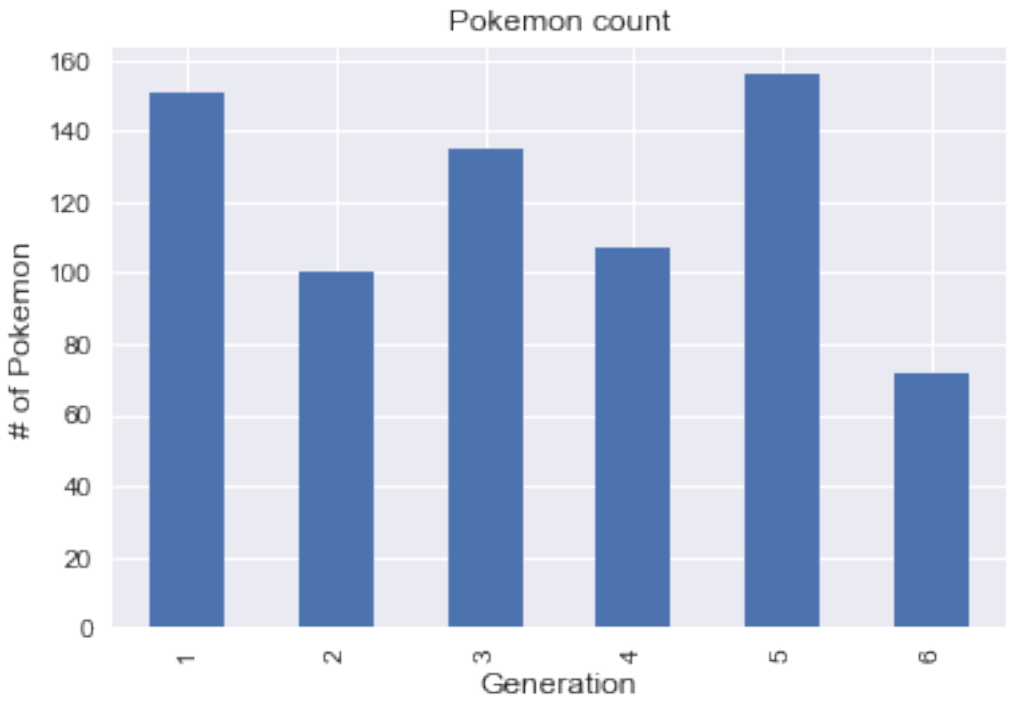
```
In [32]: # create a groupby to see below :
         description = pokedex.groupby(['generation']).describe()
         description.stack()
```

```
Out[32]:                          id
generation
1          count  151.000000
           mean    76.000000
           std     43.734045
           min      1.000000
           25%     38.500000
           50%     76.000000
           75%    113.500000
           max    151.000000
2          count  100.000000
           mean   201.500000
           std     29.011492
           min    152.000000
           25%    176.750000
           50%    201.500000
```

```
                75%    226.250000
                max    251.000000
          3     count  135.000000
                mean   319.000000
                std     39.115214
                min    252.000000
                25%    285.500000
                50%    319.000000
                75%    352.500000
                max    386.000000
          4     count  107.000000
                mean   440.000000
                std     31.032241
                min    387.000000
                25%    413.500000
                50%    440.000000
                75%    466.500000
                max    493.000000
          5     count  156.000000
                mean   571.500000
                std     45.177428
                min    494.000000
                25%    532.750000
                50%    571.500000
                75%    610.250000
                max    649.000000
          6     count   72.000000
                mean   685.500000
                std     20.928450
                min    650.000000
                25%    667.750000
                50%    685.500000
                75%    703.250000
                max    721.000000
```

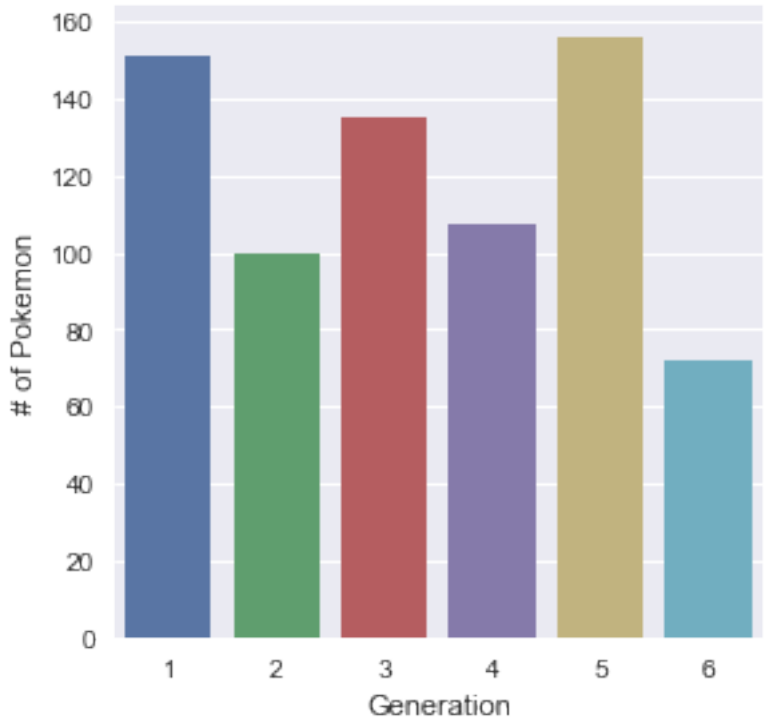
In [33]:
```
%matplotlib inline
# create plot below :
import matplotlib.pyplot as plt
ax = description[('id', 'count')].plot(kind='bar',title ="Pokemon count")
ax.set_xlabel("Generation", fontsize=12)
ax.set_ylabel("# of Pokemon", fontsize=12)
```

Out[33]:
```
<matplotlib.text.Text at 0x143bfa0bf98>
```



0.2.3 Try Seaboarn:

```
In [34]: import seaborn as sb

In [35]: sb.factorplot(kind='count', data=pokedex, x='generation').set_axis_labels("Generation

Out[35]: <seaborn.axisgrid.FacetGrid at 0x143bfc4d3c8>
```

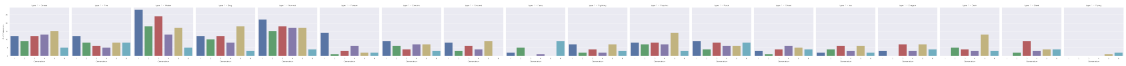


There doesn't seem to be a trend across generations; however, even-numbered generations introduced fewer Pokemon as compared to the odd-numbered generations.

Let's dig a bit deeper and examine the distribution of primary types of Pokemon across generations.

```
In [36]: sb.factorplot(kind='count',
                       data=pokedex,
                       col='type 1',
                       x='generation').set_axis_labels("Generation", "# of Pokemon")
```

```
Out[36]: <seaborn.axisgrid.FacetGrid at 0x143be09b630>
```



```
In [37]: # Add col_wrap option to the above to get below (look into sb.factorplot documentatio
         sb.factorplot(kind='count',
                       data=pokedex,
                       col='type 1',col_wrap=4,
                       x='generation').set_axis_labels("Generation", "# of Pokemon")
```

Out[37]: <seaborn.axisgrid.FacetGrid at 0x143bf99db38>

In [38]: *#Summarize your observations/conclusions here :*
#1. There are more pokemons for all generations in water
#2. The flying type pokemons are the least

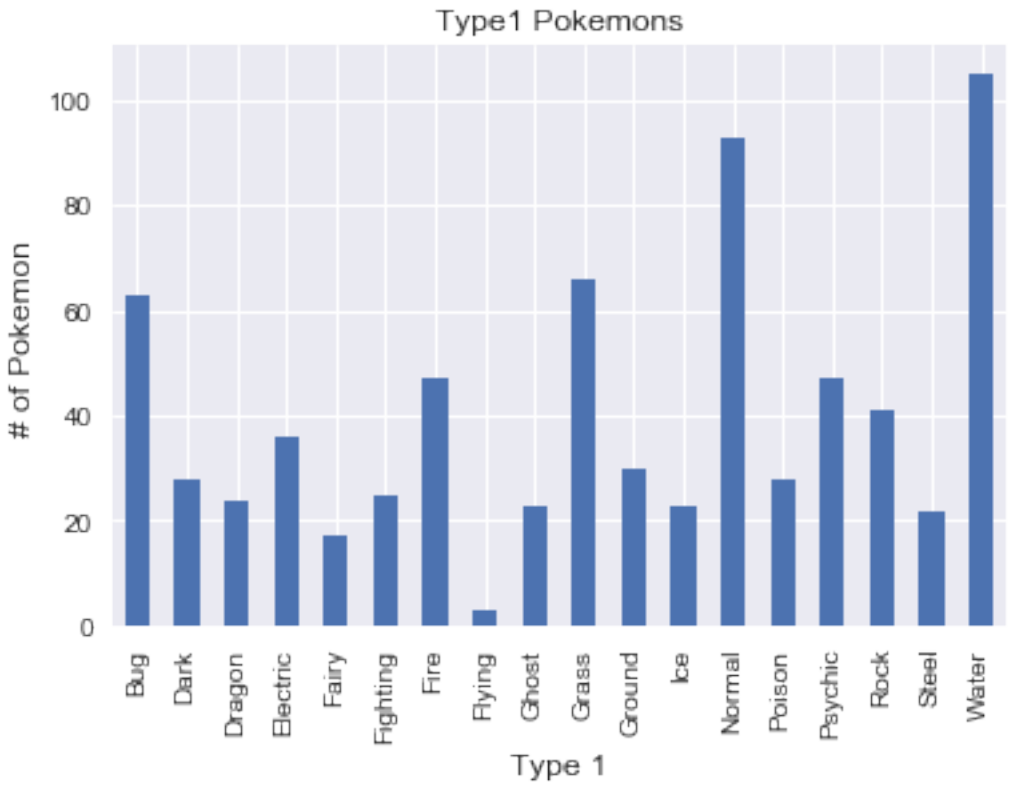
```
#3. The highest number of pokemons are of Generation 1 and type water
#4. The Generation 1 pokemon seems to be the most common
```

0.2.4 Are there unique primary or secondary Pokemon types, or if they simply share the same ones.

```
In [26]: import numpy as np
         ?np.setdiff1d  #Return the sorted, unique values in `ar1` that are not in `ar2`.

In [39]: unique_type1 =  np.setdiff1d(pokedex['type 1'], pokedex['type 2'])
         unique_type1

Out[39]: array([], dtype=object)

In [40]: unique_type2 =  np.setdiff1d(pokedex['type 2'], pokedex['type 1'])
         unique_type2

Out[40]: array(['None'], dtype=object)

In [27]: ### There are no unique primary or secondary types

In [41]: # Get The total number of primary and secondary types:
         #df = pd.DataFrame(pokedex)
         #dff = pd.DataFrame(poke_statistics)
         #df.to_excel('pokedex.xlsx')
         #dff.to_excel('poke_statistics.xlsx')
         type_1 = len(pokedex['type 1'].unique())
         type_2 = len(pokedex['type 2'].unique())
         print("# of Type1 Pokemon: "+ str(type_1))
         print("# of Type2 Pokemon: "+ str(type_2))

# of Type1 Pokemon: 18
# of Type2 Pokemon: 19
```

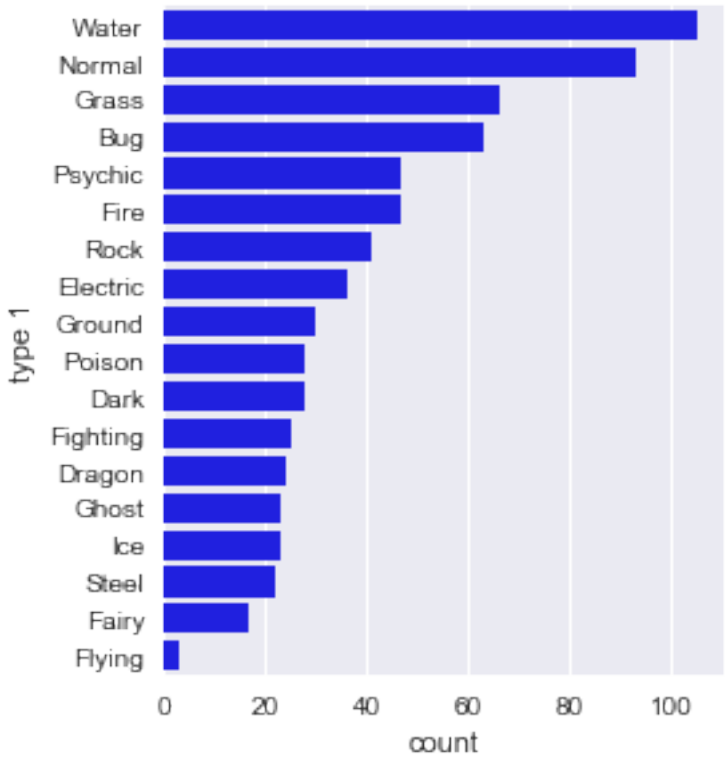
0.2.5 What are the most common types of Pokemon?

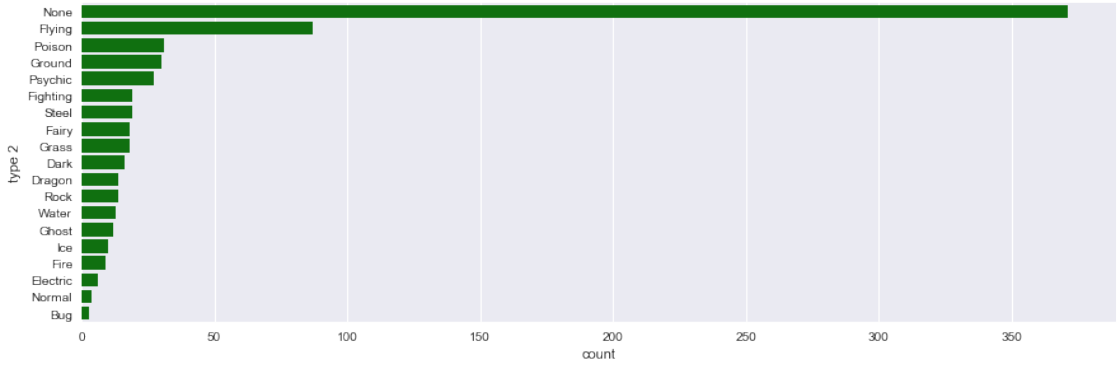
```
In [42]: # Make a plot of the distribution of the Type 1 Pokemon.
         pokedex = pd.DataFrame(pokedex)
         ax = pokedex.groupby(['type 1'])['name'].nunique().plot(kind='bar',title ="Type1 Poke
         ax.set_xlabel("Type 1", fontsize=12)
         ax.set_ylabel("# of Pokemon", fontsize=12)

         # You should see something like the plot below. Sort the DB so that we see it in an a

Out[42]: <matplotlib.text.Text at 0x143c3a9f940>
```



In [43]:
```
# Now try Seaborn:
sb.factorplot(data=pokedex,
                    y='type 1',
                     kind='count',
                      order = pokedex['type 1'].value_counts().index,
                      color='blue',
                          aspect=1)

sb.factorplot(data=pokedex,
                    y='type 2',
                     kind='count',
                      order = pokedex['type 2'].value_counts().index,
                      color='green',
                          aspect=3.1)
```

Out[43]: <seaborn.axisgrid.FacetGrid at 0x143c317f0f0>





In [44]:
```
#Summarize your observations/conclusions here :
#1. Wter is the highest number of pokemon in type 1 and the highest overall
#2. Seems to be a lognormal distribution for the different types
#3. Flying is the highest number of pokemon in type2
#4. Lots of pokemons in type 1 do not have type 2
#5. There seems to be an inverse relationship between types. The highest in type 2 (F
# and the higher types in type 1(Normal,Bug, fire) are on the lower ends in type 2
```

0.2.6 But we can not say which type maps into which type !

Lets create a heatmap !

```
In [45]: # Create a new df called "dual_types" by getting rid of the records for which we do n
         dual_types = pokedex[pokedex['type 2']!= "None"]
         dual_types
```

Out[45]:

	id	name	type 1	type 2	generation	legendary
0	1	Bulbasaur	Grass	Poison	1	False
1	2	Ivysaur	Grass	Poison	1	False
2	3	Venusaur	Grass	Poison	1	False
6	6	Charizard	Fire	Flying	1	False
15	12	Butterfree	Bug	Flying	1	False
16	13	Weedle	Bug	Poison	1	False
17	14	Kakuna	Bug	Poison	1	False
18	15	Beedrill	Bug	Poison	1	False
20	16	Pidgey	Normal	Flying	1	False
21	17	Pidgeotto	Normal	Flying	1	False
22	18	Pidgeot	Normal	Flying	1	False
26	21	Spearow	Normal	Flying	1	False
27	22	Fearow	Normal	Flying	1	False
36	31	Nidoqueen	Poison	Ground	1	False
39	34	Nidoking	Poison	Ground	1	False
44	39	Jigglypuff	Normal	Fairy	1	False
45	40	Wigglytuff	Normal	Fairy	1	False
46	41	Zubat	Poison	Flying	1	False
47	42	Golbat	Poison	Flying	1	False
48	43	Oddish	Grass	Poison	1	False
49	44	Gloom	Grass	Poison	1	False
50	45	Vileplume	Grass	Poison	1	False
51	46	Paras	Bug	Grass	1	False
52	47	Parasect	Bug	Grass	1	False
53	48	Venonat	Bug	Poison	1	False
54	49	Venomoth	Bug	Poison	1	False
67	62	Poliwrath	Water	Fighting	1	False
75	69	Bellsprout	Grass	Poison	1	False
76	70	Weepinbell	Grass	Poison	1	False
77	71	Victreebel	Grass	Poison	1	False
..	...	...	...	...	...	...
748	679	Honedge	Steel	Ghost	6	False
749	680	Doublade	Steel	Ghost	6	False
750	681	AegislashBlade Forme	Steel	Ghost	6	False
756	686	Inkay	Dark	Psychic	6	False
757	687	Malamar	Dark	Psychic	6	False
758	688	Binacle	Rock	Water	6	False
759	689	Barbaracle	Rock	Water	6	False
760	690	Skrelp	Poison	Water	6	False
761	691	Dragalge	Poison	Dragon	6	False

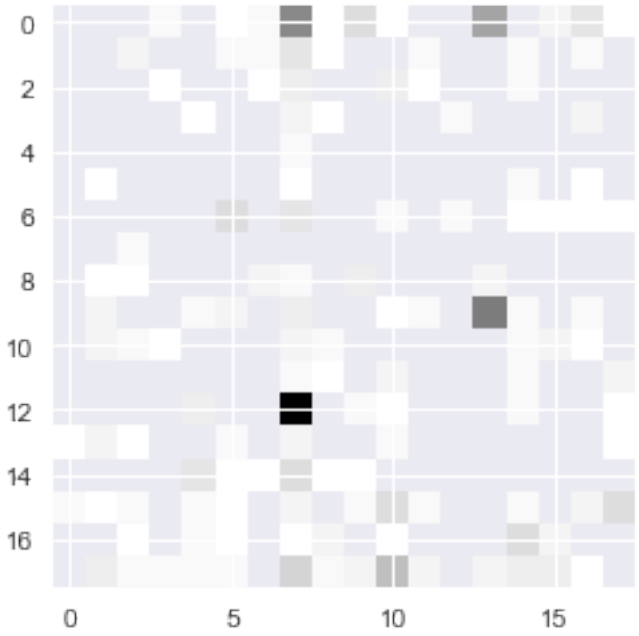
```
764  694             Helioptile  Electric    Normal           6      False
765  695              Heliolisk  Electric    Normal           6      False
766  696                 Tyrunt      Rock    Dragon           6      False
767  697              Tyrantrum      Rock    Dragon           6      False
768  698                 Amaura      Rock       Ice           6      False
769  699                Aurorus      Rock       Ice           6      False
771  701                Hawlucha  Fighting    Flying           6      False
772  702                Dedenne  Electric     Fairy           6      False
773  703                Carbink      Rock     Fairy           6      False
777  707                 Klefki     Steel     Fairy           6      False
778  708              Phantump     Ghost     Grass           6      False
779  709             Trevenant     Ghost     Grass           6      False
780  710  PumpkabooAverage Size     Ghost     Grass           6      False
784  711  GourgeistAverage Size     Ghost     Grass           6      False
790  714                 Noibat    Flying    Dragon           6      False
791  715                Noivern    Flying    Dragon           6      False
793  717                Yveltal      Dark    Flying           6       True
794  718       Zygarde50% Forme    Dragon    Ground           6       True
795  719                Diancie      Rock     Fairy           6       True
797  720    HoopaHoopa Confined   Psychic     Ghost           6       True
799  721             Volcanion      Fire     Water           6       True

[350 rows x 6 columns]
```

```
In [47]: # Get a grid of values from 'type 1' 'type 2'  (Hint: use groupby, size, unstack, val
         #and any other attributes you may need !)
         (dual_types['type 1'].unique().size,dual_types['type 2'].unique().size)
```

```
Out[47]: (18, 18)
```

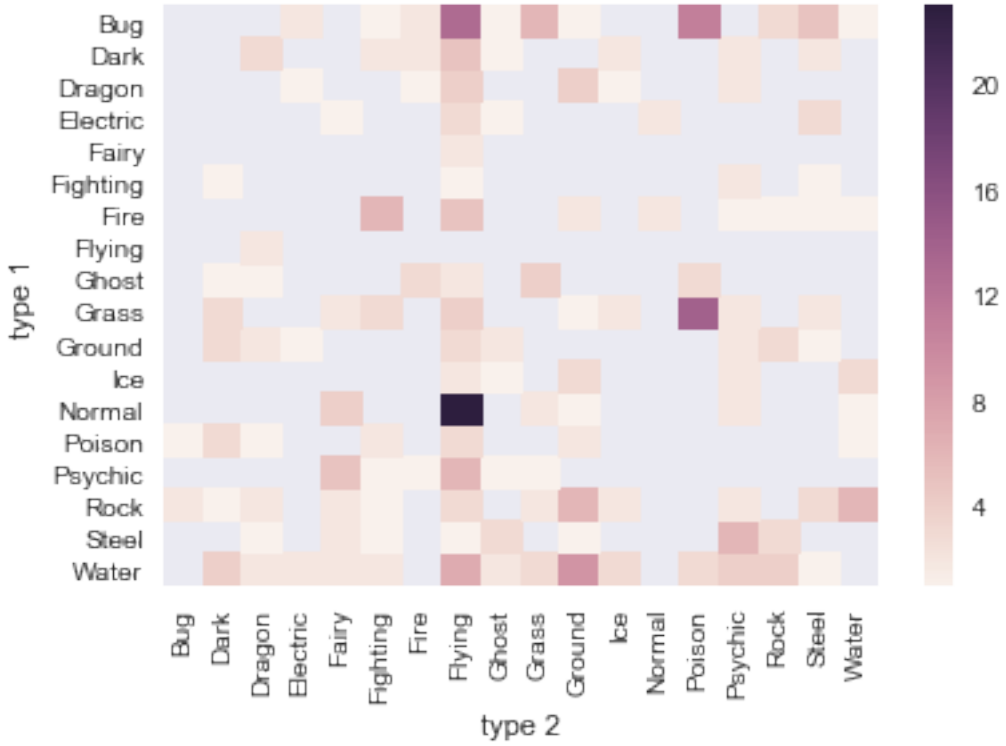
```
In [48]: # Try matplotlib imshow as a way to get a heatmap, something like this:
         import seaborn as sns
         %matplotlib inline
         #data = dual_types[['type 1', 'type 2']]
         data = dual_types.groupby(['type 1', 'type 2']).count()['id']
         data = data.unstack()
         plt.imshow(data)
```

```
Out[48]: <matplotlib.image.AxesImage at 0x143c343eeb8>
```



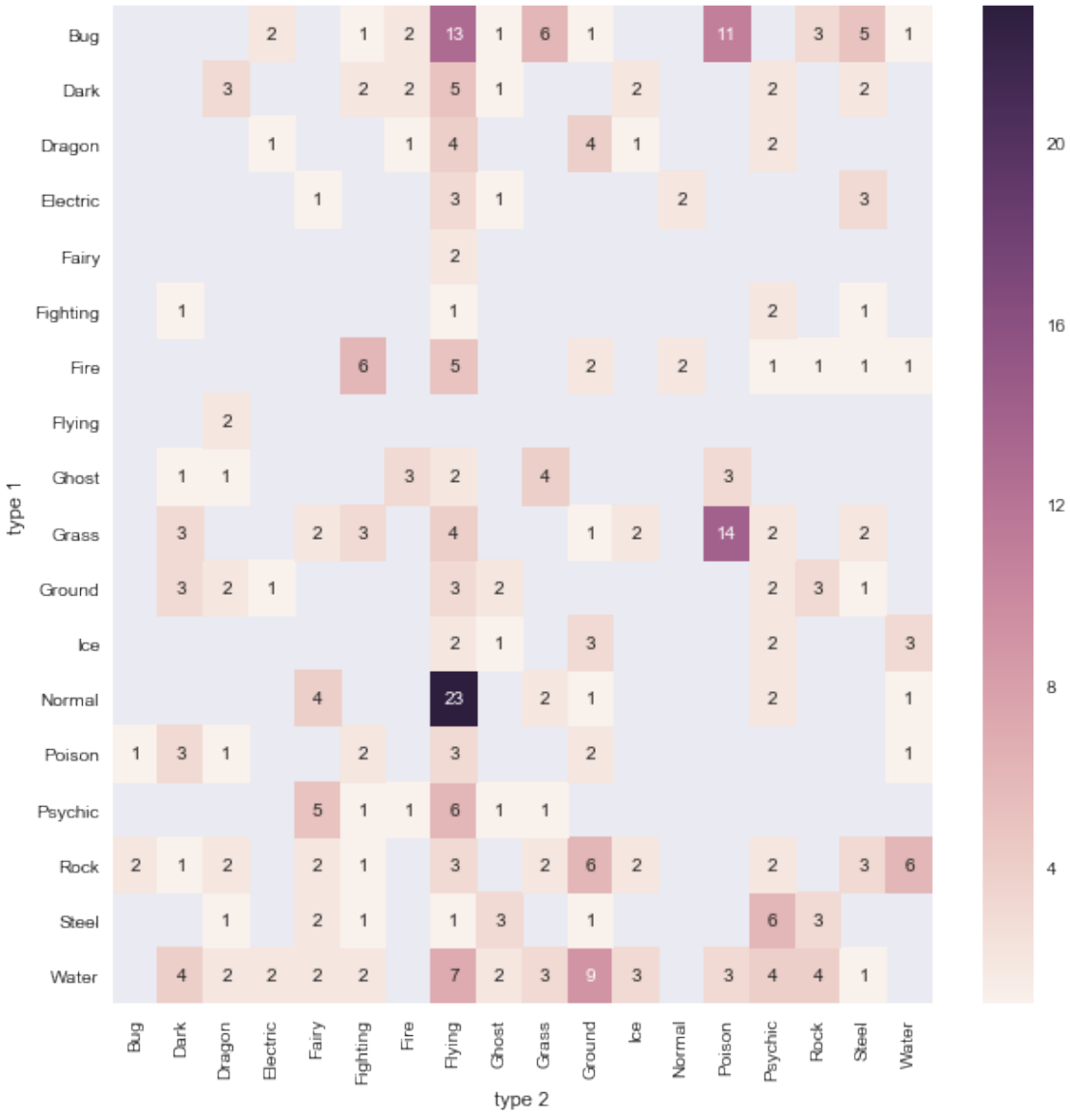
In [49]:
```
# Obviously, the plot is not very nice !
# Use seaborn heatmap option to get something like this :
sns.heatmap(data)
```

Out[49]: <matplotlib.axes._subplots.AxesSubplot at 0x143c345f1d0>



In [50]:
```
# Refine your seaborn expression to get a better heatmap :
plt.figure(figsize=(10, 10))
sns.heatmap(data, annot = True)
```

Out[50]: <matplotlib.axes._subplots.AxesSubplot at 0x143c3580be0>



In [51]:
```
#Summarize your observations/conclusions here :
# Normal and Flying occur together in type 1 and type 2 simultaneously more frequentl
#These two would have the highest correlation.
```

0.2.7 Are any of the statistics correlated?

In [52]:
```
# It is a very natural question to ask.
# plot differernt combinations of quantities and see if you can see any correlation.
# It is a very natural question to ask.
# plot differernt combinations of quantities and see if you can see any correlation.
sns.regplot(x=poke_statistics["hp"], y=poke_statistics["attack"], fit_reg=False)
#There is some correlation between "hp" and "attack"
```

Out[52]: <matplotlib.axes._subplots.AxesSubplot at 0x143c33a9be0>

In [55]:
```
# It seems hard to see the correlation based on the scatter plots.

# Instead, use "pearsonr" function from scipy's "stats" library to compute the correl
from scipy import stats
?stats.pearsonr
```

In [58]:
```
# Loop over all combinations and output the correlation coefficients. Then sort based
# Loop over all combinations and output the correlation coefficients. Then sort based
corr_coeffs =[]
cols =['hp', 'attack', 'defense', 'sp. atk', 'sp. def', 'speed']
for column_x in poke_statistics.columns:
    for column_y in poke_statistics.columns:
        corr = stats.pearsonr(x=poke_statistics[column_x],y=poke_statistics[column_y])
        corr_coeffs.append(corr[0])
coeffs= [float(x) for x in corr_coeffs]
```

```
coeffs.sort()
pd.DataFrame(coeffs)
```

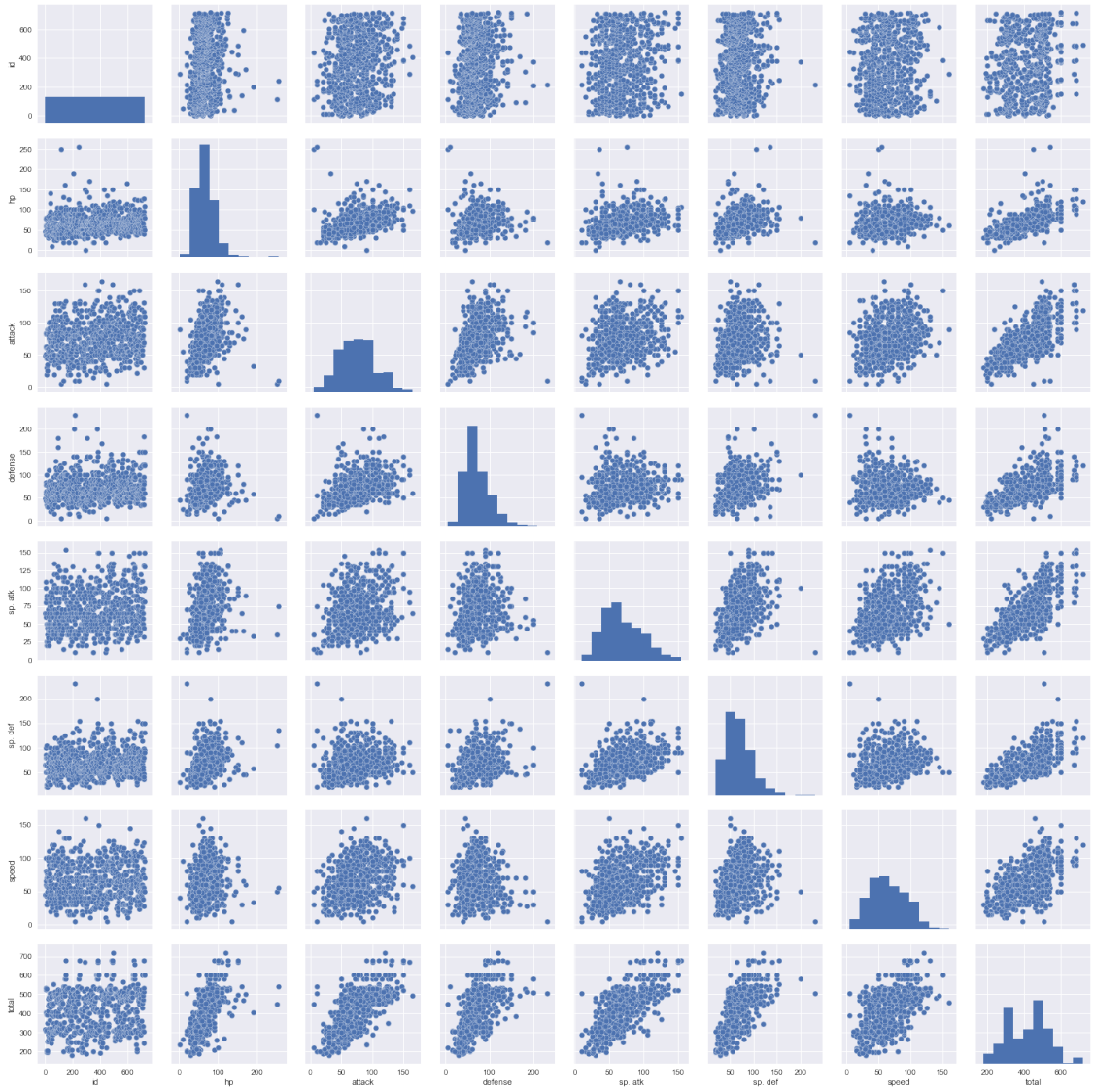
Out[58]:

	0
0	-0.006849
1	-0.006849
2	0.028156
3	0.028156
4	0.104998
5	0.104998
6	0.107512
7	0.107512
8	0.115090
9	0.115090
10	0.126503
11	0.126503
12	0.144459
13	0.144459
14	0.160370
15	0.160370
16	0.170031
17	0.170031
18	0.202188
19	0.202188
20	0.208322
21	0.208322
22	0.234177
23	0.234177
24	0.236499
25	0.236499
26	0.332172
27	0.332172
28	0.339699
29	0.339699
..	...
34	0.425839
35	0.425839
36	0.434022
37	0.434022
38	0.439548
39	0.439548
40	0.479991
41	0.479991
42	0.493038
43	0.493038
44	0.548890
45	0.548890
46	0.605786

```
47  0.605786
48  0.642628
49  0.642628
50  0.704247
51  0.704247
52  0.707223
53  0.707223
54  0.723143
55  0.723143
56  1.000000
57  1.000000
58  1.000000
59  1.000000
60  1.000000
61  1.000000
62  1.000000
63  1.000000

[64 rows x 1 columns]
```

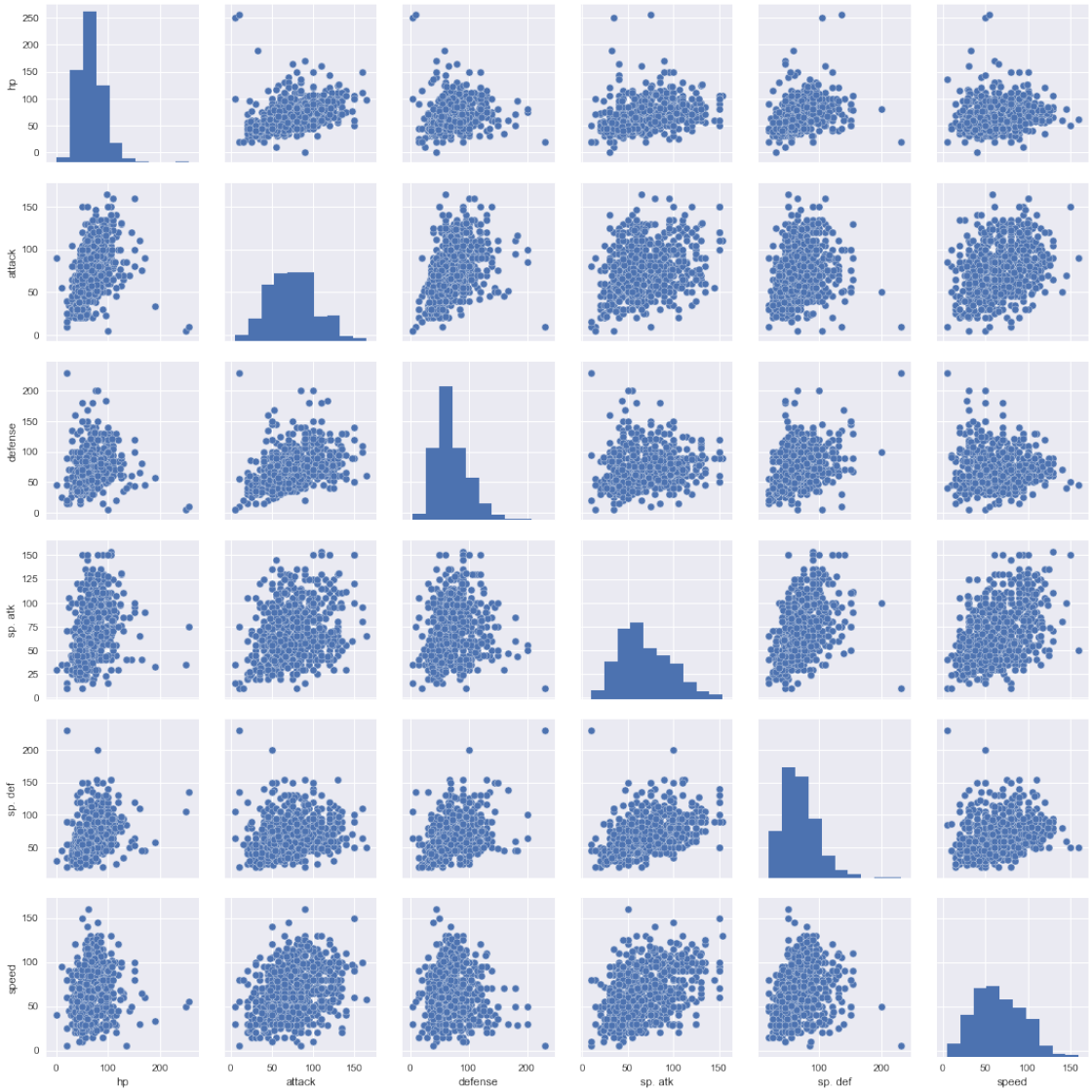
In [59]:
```
# Nothing is better than a good visualization.
# Try seaborn's pairplot to get something like this :
# Nothing is better than a good visualization.
# Try seaborn's pairplot to get something like this :
sns.pairplot(poke_statistics)
```

Out[59]:
```
<seaborn.axisgrid.PairGrid at 0x143c54180b8>
```



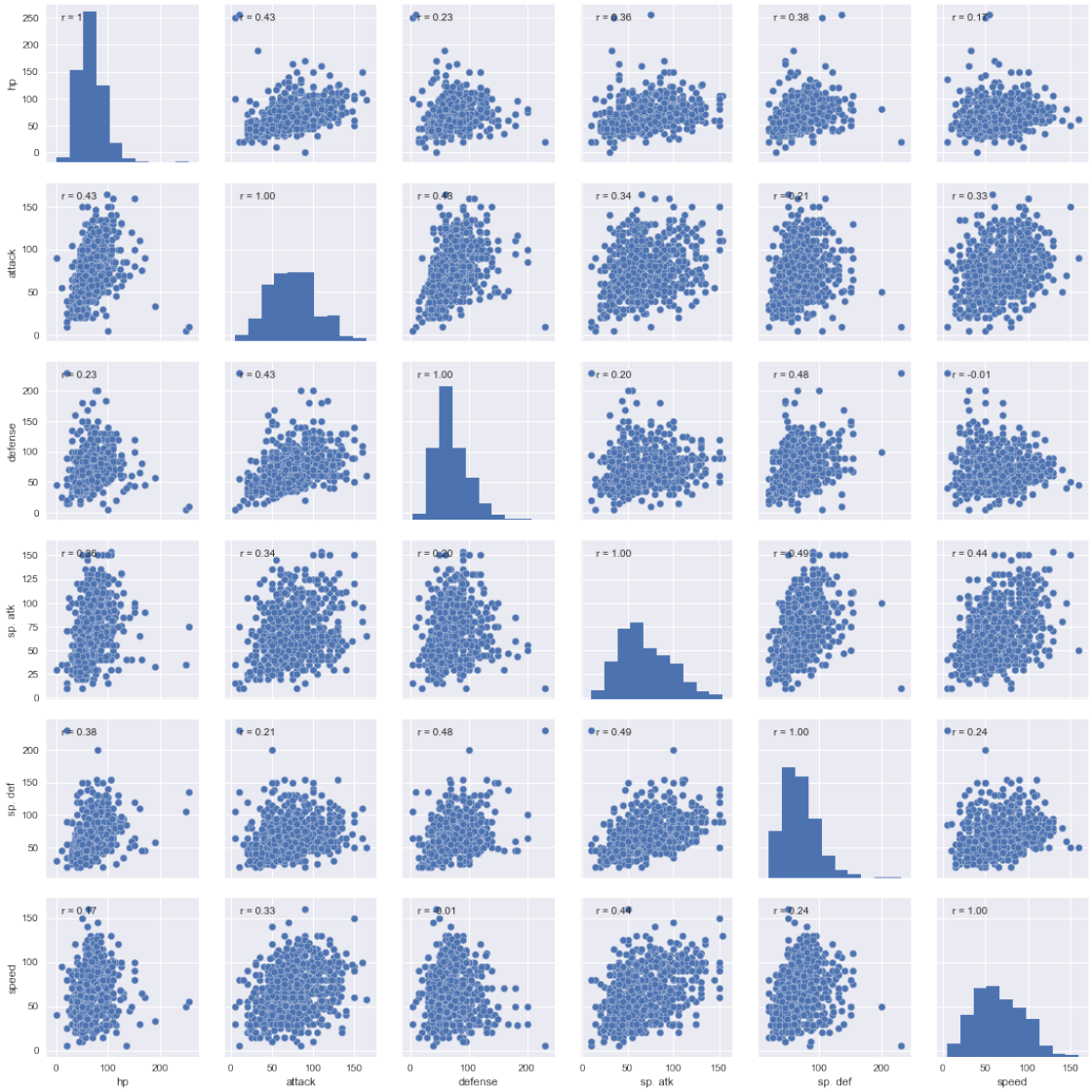

```
In [60]: # Get rid of extra columns :
         # Get rid of extra columns :
         cols = ['hp','attack','defense','sp. atk','sp. def', 'speed']
         sns.pairplot(poke_statistics[cols])
```

```
Out[60]: <seaborn.axisgrid.PairGrid at 0x143c6564f28>
```




```
In [61]: # See if you can refine your code to get this :
         # See if you can refine your code to get this :
         def corrfunc(x, y, **kws):
             r, _ = stats.pearsonr(x, y)
             ax = plt.gca()
             ax.annotate("r = {:.2f}".format(r),
                         xy=(.1, .9), xycoords=ax.transAxes)

         statistics_plot = sns.pairplot(poke_statistics[cols])
         statistics_plot.map(corrfunc)
```

```
Out[61]: <seaborn.axisgrid.PairGrid at 0x143cb260710>
```




```
In [62]: #Summarize your observations/conclusions here :
         #sp.atk and sp.def have the highest correlation(0.49). The correlation between the at
         #none of the values would be redundant in characterising each pokemon.
```

0.2.8 What are the strongest and weakest Pokemon species?

```
In [63]: # Do your calculations here :
         pd.merge(pokedex, poke_statistics, on='id').sort_values('total', ascending=False).hea
         pd.merge(pokedex, poke_statistics, on='id').sort_values('total', ascending=False).tai
         #Pokemon Arceus is the strongest by a total statistic and and Pokemon Sunkem is the w
```

```
Out[63]:       id       name  type 1 type 2  generation  legendary  hp  attack  \
         9     10   Caterpie     Bug   None           1      False  45      30
```

```
264  265    Wurmple     Bug   None           3      False  45      45
400  401  Kricketot     Bug   None           4      False  37      25
297  298    Azurill  Normal  Fairy           3      False  50      20
190  191    Sunkern   Grass   None           2      False  30      30

     defense  sp. atk  sp. def  speed  total
9         35       20       20     45    195
264       35       20       30     20    195
400       41       25       41     25    194
297       40       20       40     20    190
190       30       30       30     30    180
```

In [64]:
```
# Explain why using "Total" is not the best meric ?
#From observation of the head and tail, the Pokemons cannot be properly ranked using
#as there are similar values of 680 at the head and 195 at the tail. Total values doe
#strength based on all statistics of the pokemon, there could be a bias from one stat
```

In [65]:
```
# Instead, try a different metric: standardize the six statistic columns independentl
# value into a z-score so when we do take the sum, we account for the variation in th
# its mean and standard deviation across all Pokemon species.
z_scores=poke_statistics[cols].apply(lambda x: (x - x.mean()) / x.std())
z_scores.head()
```

Out[65]:
```
         hp    attack   defense   sp. atk   sp. def     speed
0 -0.904510 -0.898676 -0.743199 -0.133184 -0.155405 -0.759379
1 -0.324201 -0.451485 -0.263664  0.385873  0.402229 -0.209484
2  0.449545  0.236501  0.421387  1.077948  1.145741  0.523710
4 -1.136634 -0.795478 -0.948714 -0.306203 -0.713039 -0.026185
5 -0.401575 -0.382687 -0.434926  0.385873 -0.155405  0.523710
```

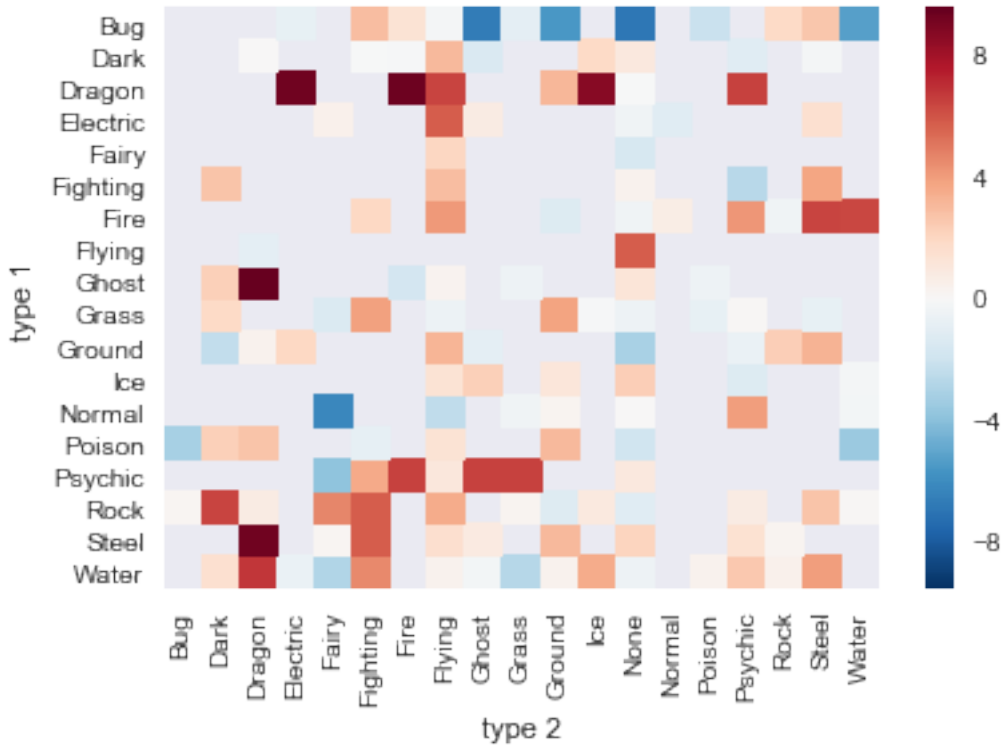
In [77]:
```
# Define a new column, strength, as the sum of the z-scores of each statisticthe high
# the stronger the Pokemon.
# Define a new column, strength, as the sum of the z-scores of each statisticthe high
# the stronger the Pokemon.
poke_statistics = poke_statistics.drop(['total'], axis=1)
poke_statistics['strength'] = z_scores.sum(axis=1).values
poke_statistics.sort_values('strength', ascending=False).head()
#Pokemon 552 is now the strongest
```

Out[77]:
```
      id   hp  attack  defense  sp. atk  sp. def  speed   strength
552  493  120     120      120      120      120    120  10.878816
544  487  150     100      120      100      120     90   9.559583
269  249  106      90      130       90      154    110   9.507000
270  250  106     130       90      110      154     90   9.471754
792  716  126     131       95      131       98     99   9.425945
```

In [78]:
```
# Repeat the heatmap you created but now for the new strength metric you computed
# Repeat the heatmap you created but now for the new strength metric you computed
full_table=pd.merge(pokedex,poke_statistics, on="id")
```

```
full_table = full_table.groupby(['type 1', 'type 2']).median().loc[:,'strength'].unsta
sns.heatmap(full_table)
```

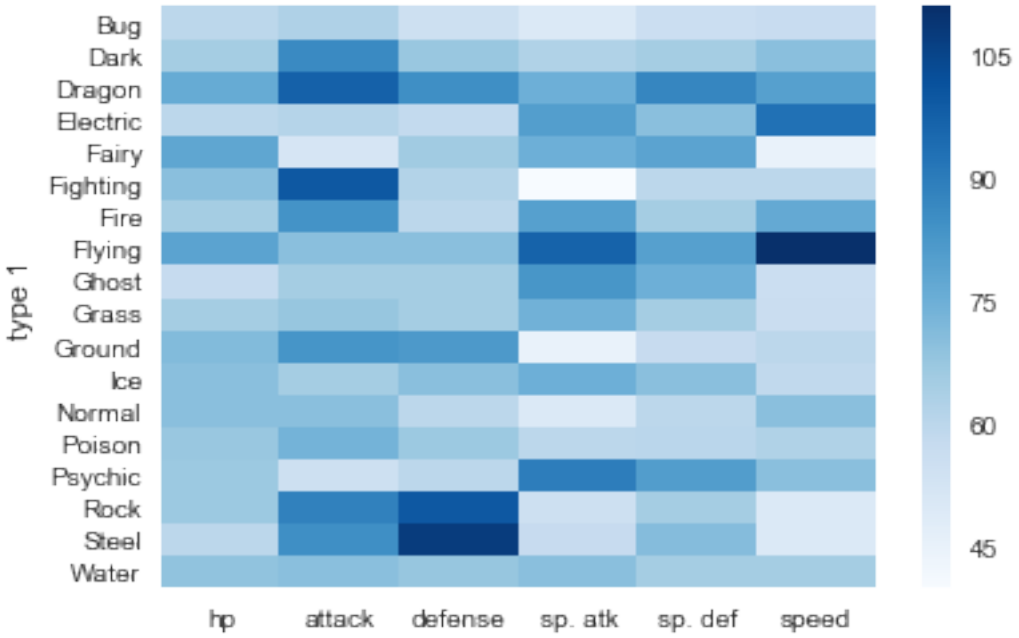
Out[78]: <matplotlib.axes._subplots.AxesSubplot at 0x143ce3f9c18>



0.2.9 Do any types of Pokemon excel at certain statistics over others?

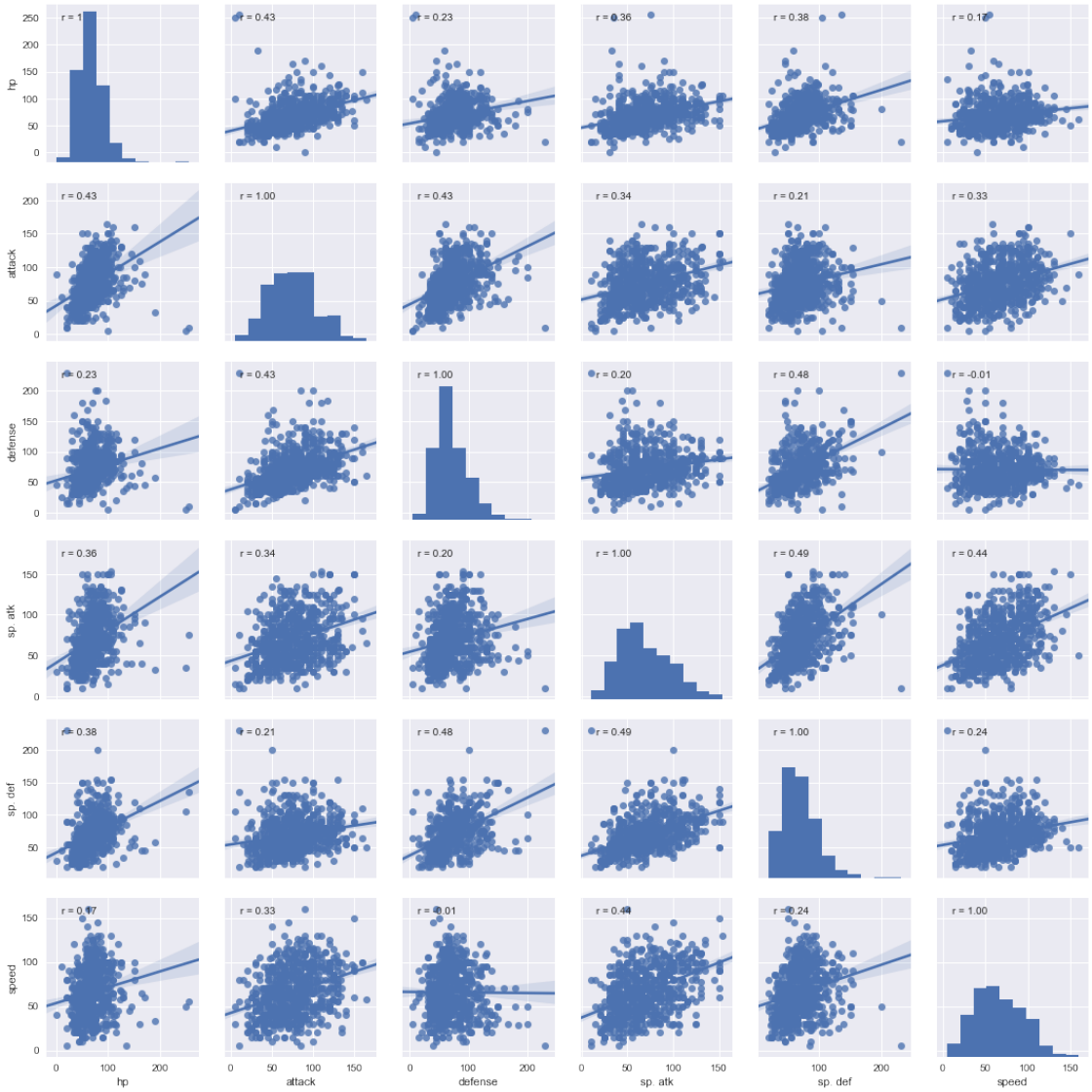
```
In [79]: # Do your calculations here. Create a heat map to show this at the end.
         full_table=pd.merge(pokedex,poke_statistics, on="id")
         check_stats = full_table.groupby(['type 1']).median().loc[:,'hp':'speed']
         sns.heatmap(check_stats,cmap="Blues")

         #Results show the flying type pokemon species have a higher speed and Rock and steel
         #are also good in attack.
```

Out[79]: <matplotlib.axes._subplots.AxesSubplot at 0x143cea95f98>



0.2.10 Are any of the statistics correlated?

```
In [80]: # Do your calculations here. Create a set of correlation plots as you did before to si
         # Do your calculations here. Create a set of correlation plots as you did before to si
         # See if you can refine your code to get this :
         def corrfunc(x, y, **kws):
             r, _ = stats.pearsonr(x, y)
             ax = plt.gca()
             ax.annotate("r = {:.2f}".format(r),
                         xy=(.1, .9), xycoords=ax.transAxes)

         g = sns.pairplot(poke_statistics[cols],kind="reg")
         g.map(corrfunc)

Out[80]: <seaborn.axisgrid.PairGrid at 0x143cebcf080>
```



In [81]:
```
# Summarize your observation here :
#Summarize your observations/conclusions here :

#sp.atk and sp.def have the highest correlation(0.49). The correlation between the at
#none of the values would be redundant in characterising each pokemon.In general the

#1. special attack/special defense
#2. defense/special defense
#3. attack/defense
#4. attack/HP
#5. special attack/speed

#And the three least correlated statistics are:
```

```
        # speed/defense
        # hp/speed
        # defense/special attack
```

In [ ]: