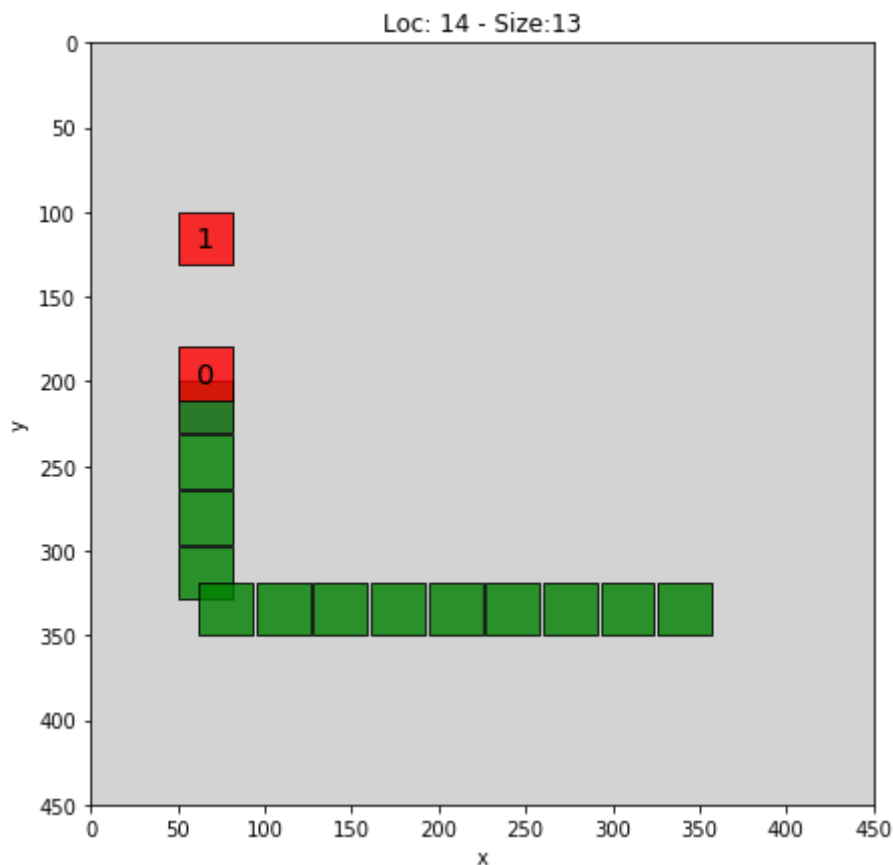


Palacing Apples in Snake - Intro

Some video-games use uniform random distribution to generate their level content. This also happens in Snake, where the location of each apple is set by calling a random generator. Because of this some apples are much easier the catch than others, or we run into sitiations where the snake doesn't even have to change directions. We can see an exmple of this in the image below:



After playing Snake for a little while (during a tutorial! I usually don't play snake for fun! :P) and having this situation happen to me a couple times I started to think about a way of choosing the location of the apple (we are going to call it placing an apple) in a smarter way by using a regression model. This model can then take into account the Snake's state (the snake's position and direction) to predict the location of the next apple. This way we avoid the situation like the one I metioned above, and also make the process of comparing the score more fair, once they are not affected by a random variable.

But this is not a conventional regression problem once there is no ground true. Each apple location is chosen randomly and therefore some apples have a good location and some others don't (By good location I mean that the apple was puted in a location that forces the player to take action). Therefore we need a way to select the good apples, so that our model can learn from them.

For this we need to score each individual random apple location, and then use that score to select what were the best apple placements. To get to this score, we are going to use several metrics that measure the quality of a placement. Keep in mind that if we want to place the apple accordingly to the snake's state, these metrics should take this state into account. I will explain these metric in more detail later.

Now that we have a data set with the best apple placements, we still have the problem that for a particular snake's state observation there are several locations that might be good to place an apple. To solve this, we are going to use this select dataset to generate several apple locations. Because these apples are generated close to the original apple, the quality of these generated locations should be close to the original selected data set. Also we are going to filter out all the generated locations that have worse metrics than the original observation.

After this all that is left to do is to use `cross_validation` to select the best model for our data set, and then test this model in our test set.

Contents:

1. Selecting and generating plays
2. Game related predictive features
3. Training, evaluation, and metrics adapted to games
4. Playing against your models! :)

Part 1: Creating a game log

For the first part we are going to create a game log. This game log will be a file where we write all the apple locations and the snake's state when this apple was placed. Since some of the variables, such as the snake's position or direction, are `list` type, I decided to use `.tsv` instead of `.csv` so that we can dump them directly as text without worrying about the commas that are present between values in a `list`. This `.tsv` will also have some other fields for the metrics that have to be captured during the game (`time_secs` and `moves_to_apple`), `time_secs` is the number of seconds since the game started and `moves_to_apple` is the number of moves a player needed to catch an apple.

This way this `.tsv` will contain the fields:

```
status|time_secs|score|moves_to_apple|apple_pos|snake_pos|snake_dir
```

During this part, one of the challenges was:

Considering a single apple, we have to save the snake's state when this apple is generated. But once we want to measure the number of moves a player took to catch this same apple, the snake state will be different at this point. We also need to save the snake state when the apple is placed in the same row as the moves it took to catch that apple. So to achieve this we have to save the snake state when the apple is placed in a separate variable, wait for the snake to catch the apple (to know how many moves it took) and then dump the saved snake state and `moves_to_apple` (or any other variable available during prediction time) in the game log file.

Part 2: Placing apples!

In this 2nd part we are going to use the data from our game log to create our metrics, select a dataset, train and test our models.

In [1]:

```
1 import matplotlib
2 import numpy as np
3 import matplotlib.pyplot as plt
4 import pandas as pd
5 import pickle
6 # Sklearn
7 from sklearn.ensemble import RandomForestRegressor, ExtraTreesRegressor
8 from sklearn import metrics
9 from sklearn.model_selection import GridSearchCV, KFold
10 # Helper funtions
11 from jupyter_utils.plots import plot_snake
12 from jupyter_utils.metrics import compute_distance, compute_all_metrics, get_n_l
13 from snake_game.features import position_norm, compute_all_feats
14 from snake_game.config import SCR_SZ
```

0 - Opening the game log

We start by opening the game log file with the apple placements

In [2]:

```
1 from jupyter_utils.parser import parse_and_preprocess_game_log
2
3 df = parse_and_preprocess_game_log("game_log_1.tsv")
4
5 # Checking the types to make sure or parsing is working
6 print(df.dtypes)
7 # Quick look into the data
8 with pd.option_context('display.max_rows',10):
9     display(df)
```

```
status          object
time_secs       float64
score           int64
moves_to_apple  int64
apple_pos       object
snake_pos       object
snake_dir       object
other           object
time_to_apple   float64
dtype: object
```

	status	time_secs	score	moves_to_apple	apple_pos	snake_pos	snake_dir	other	tin
0	start	0.000	0	0	[]	[]	[]	{}	
1	apple	2.067	0	2	[360, 130]	[[140, 280]]	[3, 0]	{}	
2	apple	4.282	0	2	[100, 250]	[[380, 148]]	[0, -3]	{}	
3	apple	5.529	1	2	[270, 240]	[[107, 220], [107, 187]]	[0, 3]	{}	
4	apple	7.432	2	3	[190, 370]	[[248, 250], [242, 277], [209, 277]]	[0, -3]	{}	
...	
1365	apple	94.875	41	2	[390, 290]	[[18, 210], [18, 243], [18, 276], [18, 309], [...]]	[0, -3]	{}	
1366	apple	97.341	42	2	[170, 300]	[[381, 261], [381, 228], [381, 195], [381, 162...]]	[0, 3]	{}	
1367	apple	102.096	43	5	[410, 40]	[[147, 309], [147, 342], [147, 375], [165, 390...]]	[0, -3]	{}	
1368	apple	107.060	44	4	[110, 200]	[[381, 18], [348, 18], [315, 18], [282, 18], [...]]	[3, 0]	{}	
1369	overS	108.811	45	2	[260, 220]	[[129, 186], [132, 216], [132, 249], [132, 282...]]	[-3, 0]	{'fin_pos': [[150, 90], [117, 90], [84, 90], [...]]}	

1370 rows × 9 columns

0.1 - Vizualizing some observations

As a helper method, I created the function `plot_snake()` (`jupyter_utils.py`). This function can be used to check the snake and apple(s) position.

It's quite useful as it allows you to visualize several placements at the same time. It helps you do simple debugging and experiment with the type of game scenarios you have in your training set. It also helps with feature engineering and to check the model's prediction.

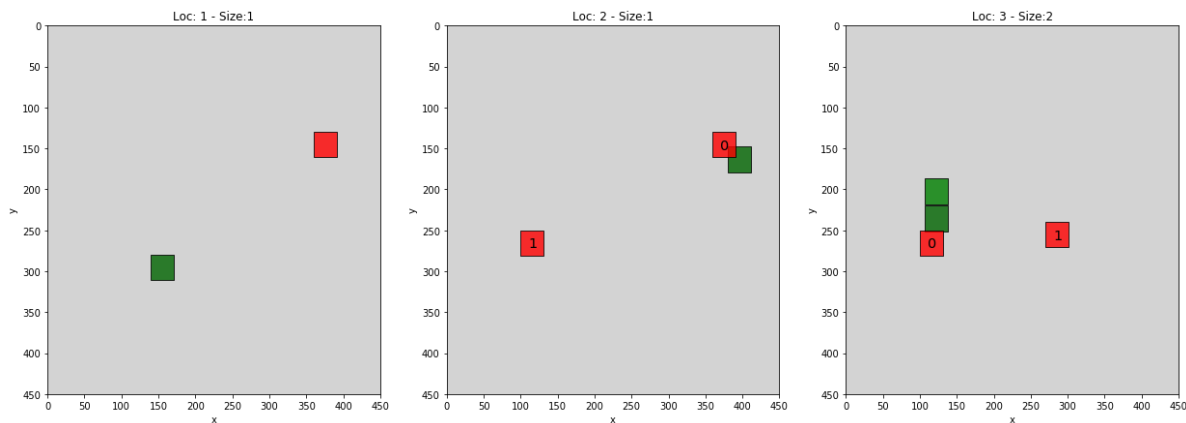
We are also adding a column that represents the position of the previous apple. This column is used in the visualization and also to make sure our game logs are correct.

In [3]:

```
1 # The position of the previous apple can be obtained by just shifting the "apple_pos"
2 df["prev_apple_pos"] = df.apple_pos.shift(1)
```

In [4]:

```
1 # Exemple on how to use plot_snake()
2 plot_snake(df.iloc[:4])
```



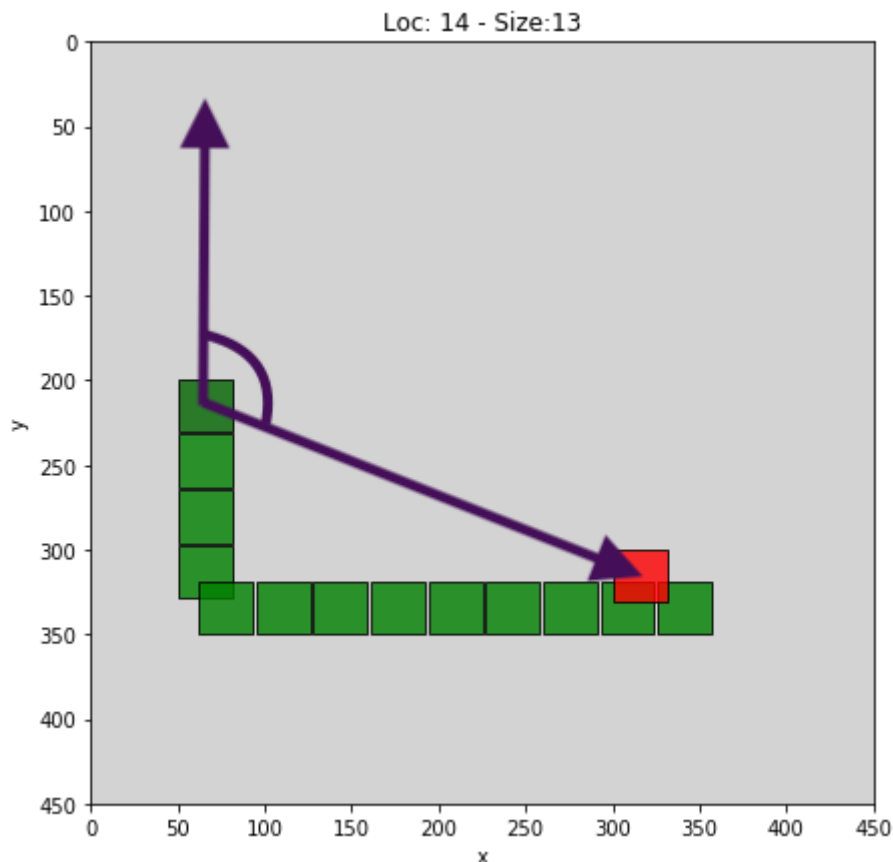
1 - Metrics to select the best apple placements

As explained before, we need to design a metric to measure the quality of each apple location, in relation with the snake's state. We have to keep in mind that there are several criteria we can use for these metrics. The behaviour of our model will be influenced by the metrics you use, since these metrics will be used to select our training set. This way different metrics can be chosen to archive different game experiments.

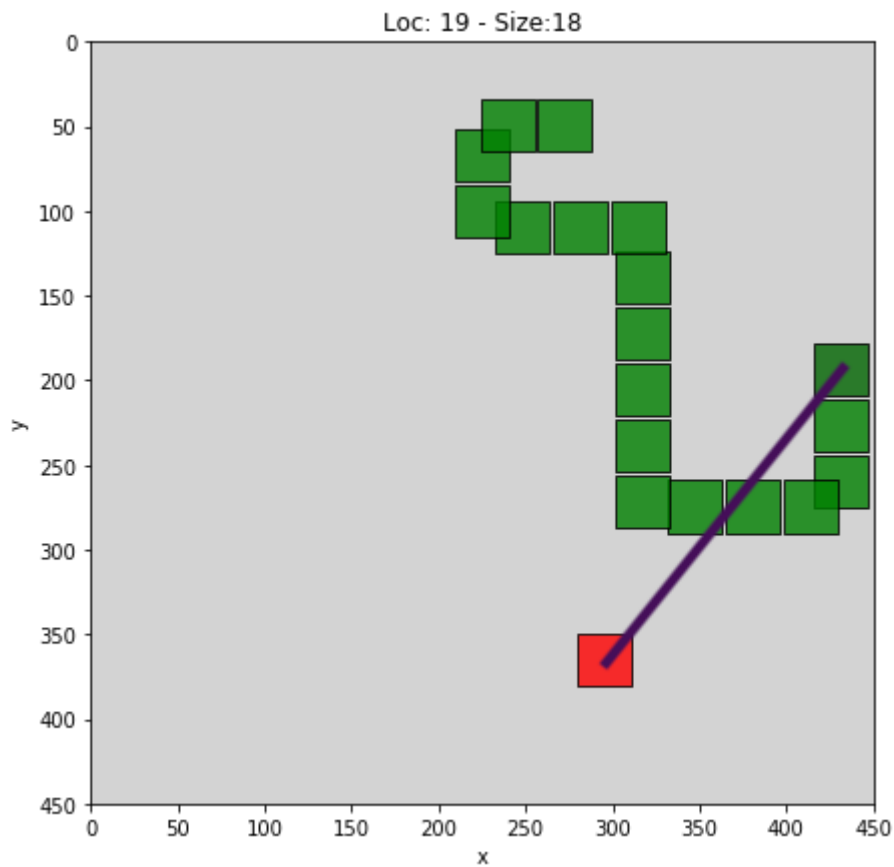
When designing these metrics, take into account that simple metrics work better once it's easier for the model to identify relations between the apple's location and the snake's state. Also you should have more than one metric, as different metrics might be useful in different stages of the game.

With this in mind let's think about some metrics that we can use:

- `time_to_apple` : The time that it takes for the snake to go from one apple to the other. The longer it takes for the snake to get to an apple, the better that apple was placed. This is not necessarily always true, especially for the beginning of the game, but as the snake grows, the snake's body gets in the way of the apple, making you take longer for apples that were not in direct reach.
- `moves_to_apple` : This is a pretty simple metric, the more moves you had to make to get the apple, the harder it was and therefore the better that apple was placed.
- `apple_dist` : The distance between the apple and the snake's mouth. This metric aims to penalize apples that were too close to the snake. Not all the apples that are close to the snake are bad, but we can detect those with other metrics.
- `snake_dir_to_apple_angle` : The angles between the snake's direction and the apple. The higher this angle is the more moves the player will have to do, as the snake needs to change its direction.



- `num_intersections_w_snake` : The number of times that a straight line from the apple to the snake's mouth intersects the snake's body. If there is an intersection, this means that the snake can not go directly towards the apple (as we can see in the image below), and therefore demands more moves, making it harder to get the apple. In the example below it's 1.



Below we will calculate these metrics.

In [5]:

```
1 metrics_df = df[df.status != 'start'].drop("other", axis=1).copy()
2 metrics_df = compute_all_metrics(metrics_df)
3 metrics_df.head()
```

Out[5]:

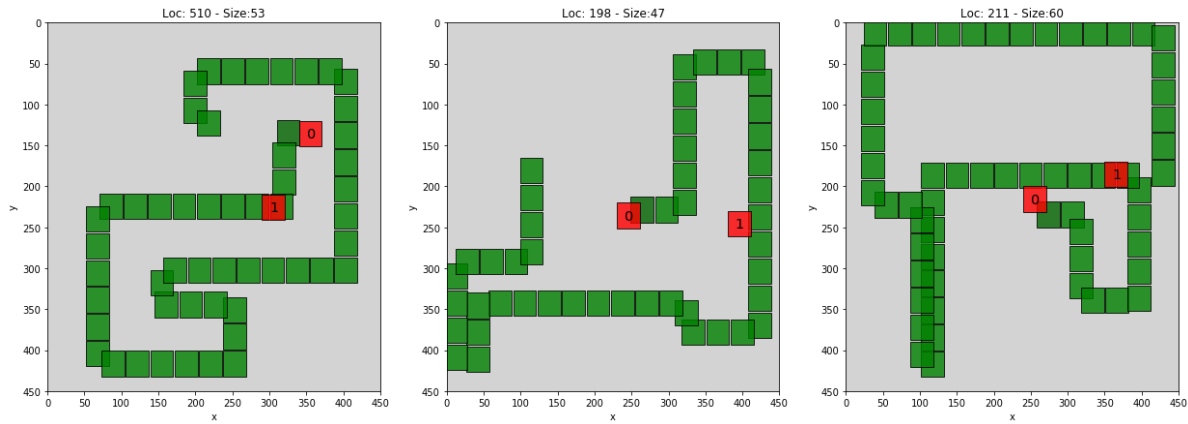
	status	time_secs	score	moves_to_apple	apple_pos	snake_pos	snake_dir	time_to_apple
1	apple	2.067	0	2	[360, 130]	[[140, 280]]	[3, 0]	2.067
2	apple	4.282	0	2	[100, 250]	[[380, 148]]	[0, -3]	2.215
3	apple	5.529	1	2	[270, 240]	[[107, 220], [107, 187]]	[0, 3]	1.247
4	apple	7.432	2	3	[190, 370]	[[248, 250], [242, 277], [209, 277]]	[0, -3]	1.903
5	apple	10.427	3	2	[370, 10]	[[194, 340], [194, 307], [194, 274], [194, 241]]	[0, 3]	2.995

Now, let's take a look at the highest top 3 cases for each metric.

As we can see, for most of these cases the apple location was not an easy one for the player.

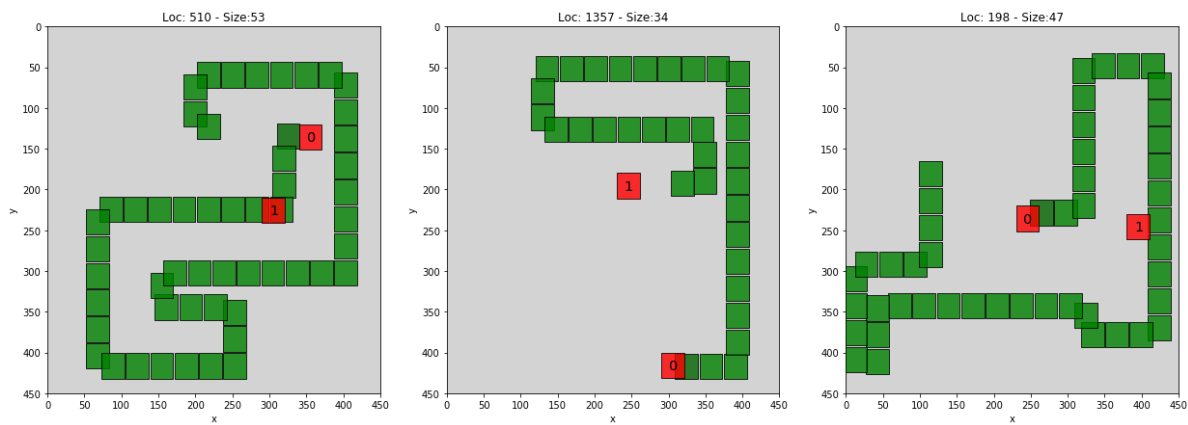
In [6]:

```
1 plot_snake(get_n_highest_rows(metrics_df, "time_to_apple"))
```



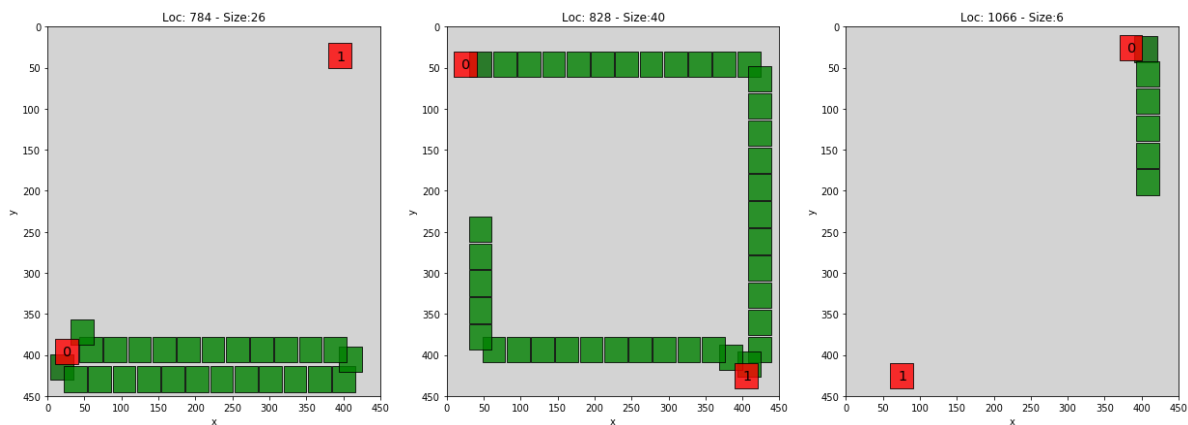
In [7]:

```
1 plot_snake(get_n_highest_rows(metrics_df, "moves_to_apple"))
```



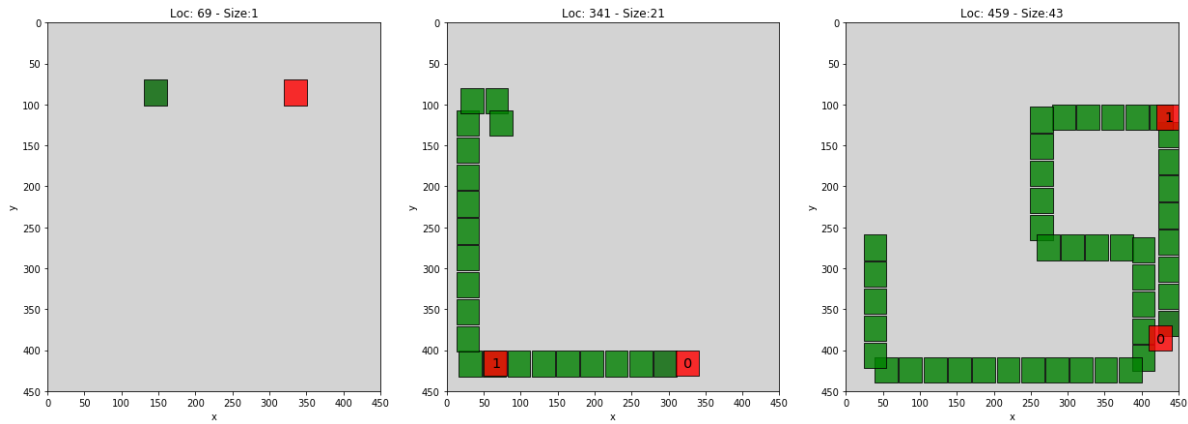
In [8]:

```
1 plot_snake(get_n_highest_rows(metrics_df, "apple_dist"))
```



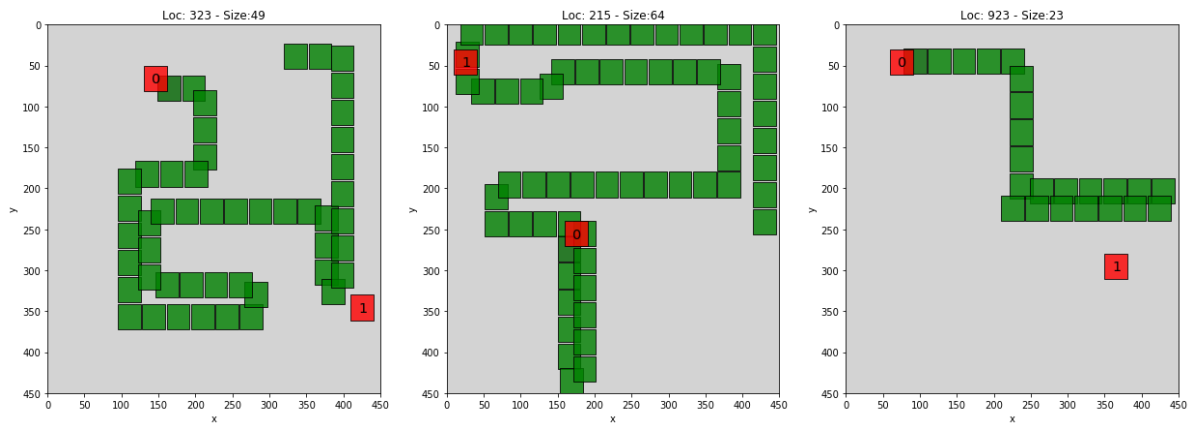
In [9]:

```
1 plot_snake(get_n_highest_rows(metrics_df, "snake_dir_to_apple_angle"))
```



In [10]:

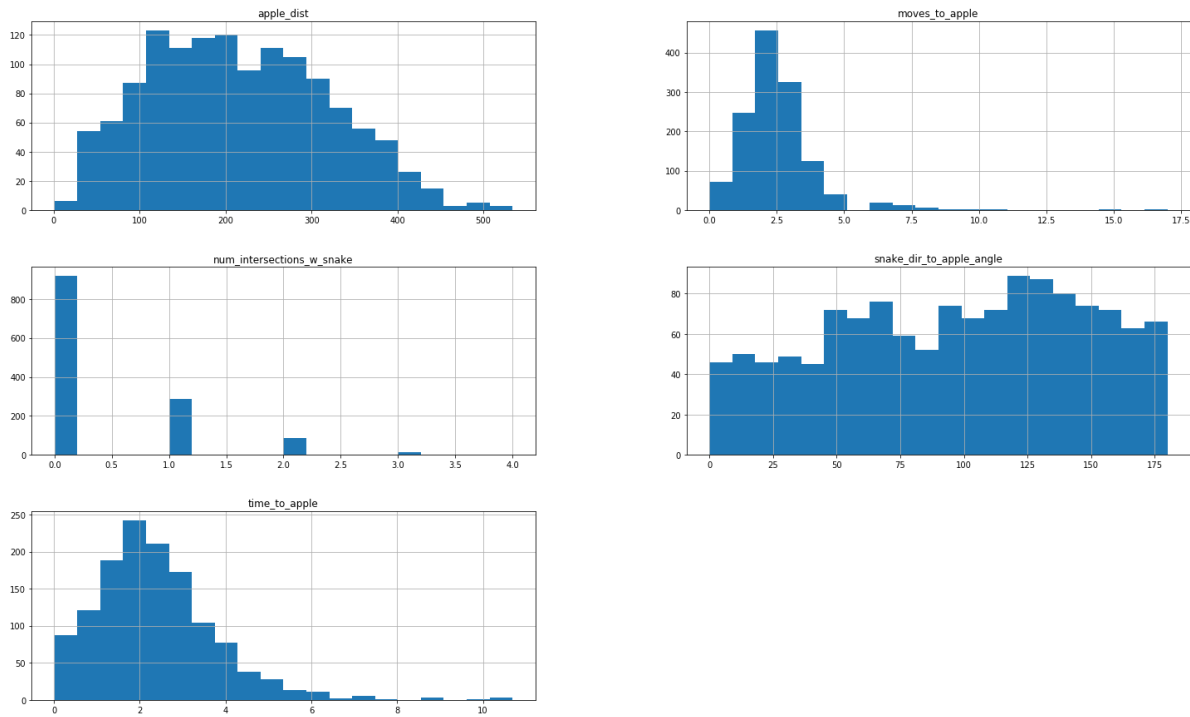
```
1 plot_snake(get_n_highest_rows(metrics_df, "num_intersections_w_snake"))
```



To make sure our metrics are correct let's take a look at their distributions.

In [11]:

```
1 metrics_columns = ["moves_to_apple", "time_to_apple",  
2                   "apple_dist", "snake_dir_to_apple_angle",  
3                   "num_intersections_w_snake"]  
4 _=metrics_df[metrics_columns].hist(bins=20,figsize=(25,15))
```



1.1 - Metric's Scores

Now that we have several metrics, we need a single value score that allows us to select the best placements. This score can also be used to compare the performance between different models and the random process.

To compute the score we are going to calculate a weighted average of the metrics we defined. We can pick different weights depending on the desired behaviour we want for our model's predictions. But keep in mind that each metric has a different scale and shape and we are including all these different metrics in a single score.

Therefore, we shouldn't average the value of the metric itself (ex: secs_to_Apple:2.3s) but the percentile. So in the end we are going to get the percentile of each observation per metric and then get the final score by averaging these percentiles. This way we remove the shape and scale of each metric and have more control over the weights in the final score.

In [12]:

```
1 metrics_columns
```

Out[12]:

```
['moves_to_apple',  
 'time_to_apple',  
 'apple_dist',  
 'snake_dir_to_apple_angle',  
 'num_intersections_w_snake']
```

In [13]:

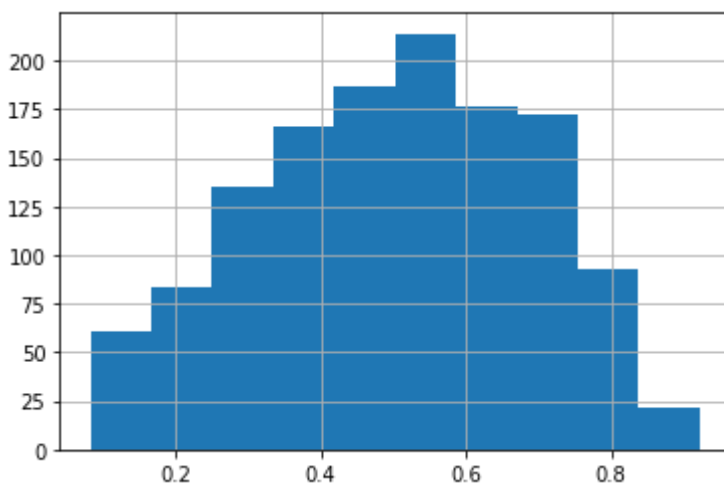
```
1 # Implementation of the score function  
2 #score_columns = ["moves_to_apple", "time_to_apple", "apple_dist", "snake_dir_to_apple"]  
3 score_weights = [1,1,1,1, 1]  
4 def score_apples_placement(df, score_columns, score_weights):  
5     score_df = df[score_columns]  
6  
7     #score_df = (score_df-score_df.min())/(score_df.max()-score_df.min())  
8     score_df = score_df.rank()/score_df.rank().max()  
9  
10    score_df["apple_plc_score"] = np.average(score_df, axis=1, weights=score_weights)  
11    return score_df["apple_plc_score"]  
12  
13 # The columns that had a weight deferent than zero during the scoring  
14 valid_filter_cols = [m for m, w in zip(metrics_columns, score_weights) if w != 0]  
15 # Calculating the scores  
16 metrics_df["apple_plc_score"] = score_apples_placement(metrics_df, metrics_columns, score_weights)
```

In [14]:

```
1 # The distribution of our scores  
2 metrics_df["apple_plc_score"].hist()
```

Out[14]:

<matplotlib.axes._subplots.AxesSubplot at 0x131369e10>



2 - Filtering Metric's Scores to create a training set

Now that we scored each apple we want to use these scores to create a training set with the best placements. Before that we are also going to select our test set, since the test set shouldn't be affected by this filtering.

In [15]:

```
1 # Pick the last 15 games
2 test_ds_start_idx = df[df.status == 'start'].iloc[-15].name
3
4 test_df = metrics_df.loc[test_ds_start_idx:].copy()
5 metrics_df = metrics_df.loc[:test_ds_start_idx]#.iloc[:-1]
```

In [16]:

```
1 # Once we used percentile for our scores, by selecting a value of
2 # 0.6 as a lower limit for our trainig set, we garanty that if one of the metric
3 # then the other is at least 0.1
4 selected_df = metrics_df[metrics_df["apple_plc_score"] >=0.65]
5 selected_df.shape
```

Out[16]:

(248, 14)

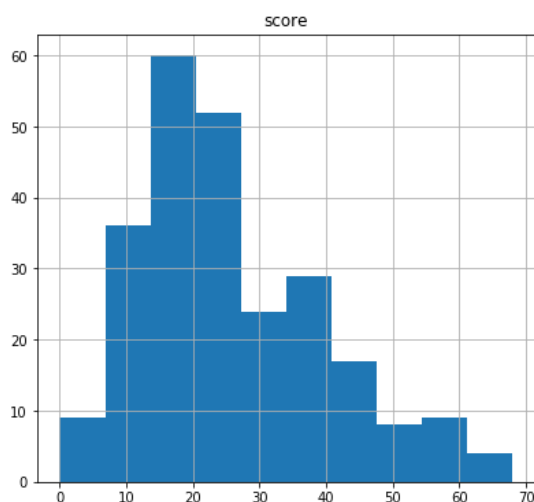
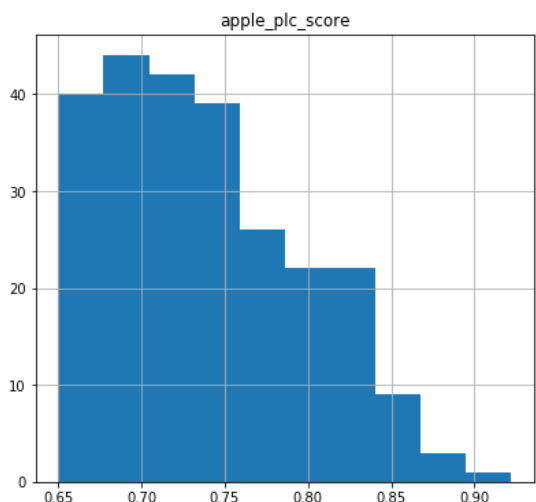
After selecting our training set we have to make sure that we have observations in all spectrums of the game score. Because, we need our model to be trained with data for all the levels (in this case score) of the game. As we can see below on the plot from the right.

In [17]:

```
1 # We should have data points in all the score range
2 selected_df[["score", "apple_plc_score"]].hist(figsize=(15,6))
```

Out[17]:

```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x12efb23c8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x132411e80
>]],
      dtype=object)
```



2.1 - Generating more apples

For each snake's state, there is more than one possible option to place a good apple. So from a single placement we are going to randomly generate several placements that are close to the original placement. Also this helps our regressor to not over fit. All the generated apple locations that have worse metric than the original observation are filtered, to make sure we don't generate observations that are worse than its original.

In [18]:

```
1 def generate_apples_from_row(row, n_try = 6):
2     ap_pos = row.apple_pos
3     rand_lim = [50,50]
4     rand_lim_min = -np.minimum(ap_pos, np.array(rand_lim))
5     rand_lim_max = np.minimum(np.array(SCR_SZ) - np.array(ap_pos), rand_lim)
6
7     randa = np.stack((
8         np.random.randint(rand_lim_min[0], rand_lim_max[0], size=(n_try,)),
9         np.random.randint(rand_lim_min[1], rand_lim_max[1], size=(n_try,))
10    ), axis=1)
11
12    new_ap_pos = ap_pos+randa
13
14    new_apples_df = pd.DataFrame(n_try*[row])
15    new_apples_df["apple_pos"] = new_ap_pos.tolist()
16    new_apples_df["apple_pos"] = new_apples_df["apple_pos"].apply(np.array)
17
18    new_apples_df = compute_all_metrics(new_apples_df)
19    selected_new_apples_bool = (new_apples_df[valid_filter_cols] >= row[valid_f:
20    new_apples_df = new_apples_df[selected_new_apples_bool].reset_index()
21    return new_apples_df
22
23 def generate_apples(df, n_tries_per_row = 6):
24     generated_dfs = df.apply(lambda r: generate_apples_from_row(r, n_tries_per_
25     return pd.concat(generated_dfs.values, ignore_index=True)
```

In [19]:

```
1 # testing the function in a single row
2 # different runs will produnce different number of new obsevation
3 generate_apples(selected_df.iloc[:2])
```

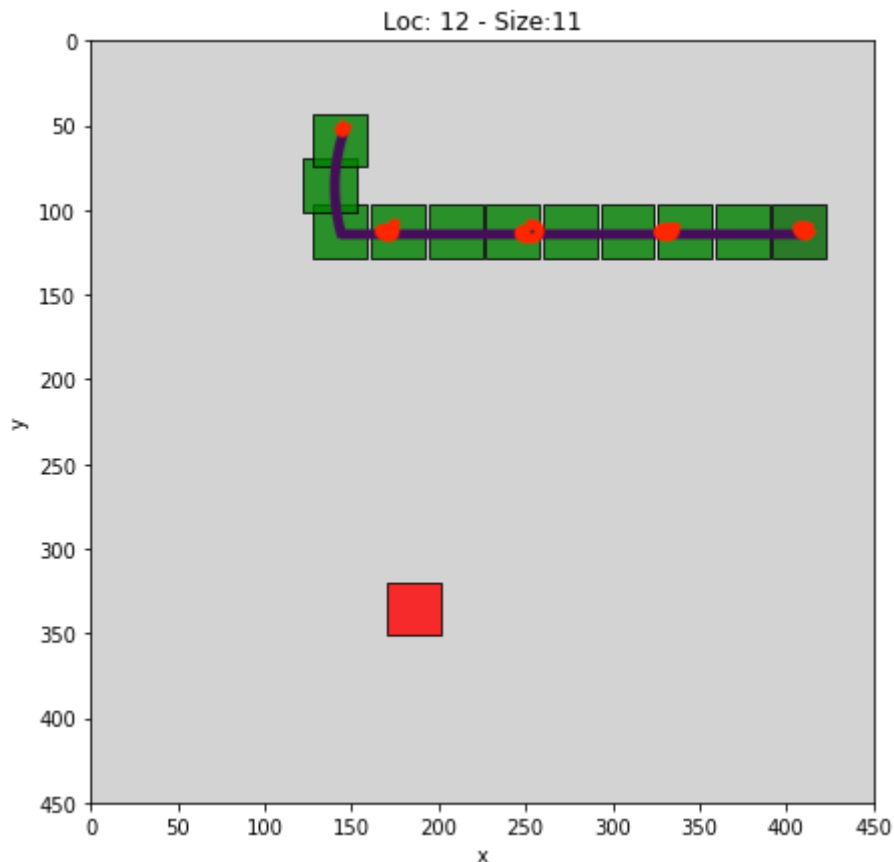
Out[19]:

index	status	time_secs	score	moves_to_apple	apple_pos	snake_pos	snake_dir	time_to_eat	
0	6	apple	14.011	4	2	[42, 402]	[[368, 28], [368, 61], [368, 94], [368, 127], ...]	[0, -3]	0.000
1	6	apple	14.011	4	2	[38, 409]	[[368, 28], [368, 61], [368, 94], [368, 127], ...]	[0, -3]	0.000

3 - Features

Once our model has to react to different states of the snake (position and direction), we need features that reflect this.

For this use directly the snake direction (as dummies) and game score. Although we can't do the same with the snake's location, since the size of the snake keeps growing as the game progresses. So we need to normalize it to a constant size. To do this consider a line that starts in the snake's mouth and ends on the tail, the last square of the snake. To normalize the snake location to an array of size N we can simply sample this line in N points. In the exemple bellow $N=5$



Besides these features I also tried to use the min, max and mean of the snake's location.

Keep in mind that since these features have to be used during the game, we need to declare them outside this notebook, by defining them in the `snake_game/features.py` file. Also, because the feature are going to be computed during gameplay, we should keep performace in mind. For this I avoided using `pandas` and tried to use `numpy` as much as possible, even though in this particular case we are talking about snake!

In [20]:

```
1 feat_df = selected_df.copy()
2 # todo move to pre procc and solve game bug
3 feat_df.loc[(feat_df.score==0), "snake_dir"] = [[np.array([0,0])]]
4
5 feat_df = feat_df.apply(lambda r: pd.Series(compute_all_feats(r["snake_pos"], r["snake_dir"], r["apple_pos"])), axis=1)
6 feat_df["apple_pos"] = selected_df["apple_pos"]
7 #feat_df = feat_df.join(pd.get_dummies(feat_df["head_ang"].apply(int), prefix="head_ang"))
8
9 feat_df.head()
```

Out[20]:

	norm_pos_0_x	norm_pos_0_y	norm_pos_1_x	norm_pos_1_y	norm_pos_2_x	norm_pos_2_y	i
5	194.0	340.0	194.00	315.25	194.0	290.5	
6	368.0	28.0	368.00	61.00	368.0	94.0	
19	416.0	178.0	356.75	259.00	302.0	173.5	
25	290.0	352.0	365.75	412.00	398.0	254.5	
27	233.0	250.0	125.75	151.00	36.5	85.0	

5 rows × 22 columns

4 - Tranning

In this final section we are going to to talk about some details we should pay attention to during cross validation and testing.

Since we are generating data that is based on other rows, we have to be careful with the way we generate new data. We have to make sure that there is no leaking between training and validation sets! For that we used `sklearn GridSearchCV` with costum folds. This way we start by using `KFold` in our selected dataset, then for each training fold we generate new data. Finally, this generated data is added to the initial training fold.

This implementation can be seen below.

In [21]:

```
1 kf = KFold(n_splits=3)
2 train_df = selected_df.copy()
3 gen_folds = []
4 for train, test in kf.split(train_df):
5     gen_df = generate_apples(train_df.iloc[train])
6
7     prev_train_df_size = train_df.shape[0]
8     train_df = train_df.append(gen_df.drop("index", axis=1), ignore_index=True,
9
10     new_train = np.array(tuple(train) + tuple(range(prev_train_df_size, train_df.
11     gen_folds.append((new_train, test))
12
13 print("GENERATED", train_df.shape[0]-selected_df.shape[0], "ENTRIES FROM", selected_df.shape[0])
```

GENERATED 655 ENTRIES FROM 248

In [22]:

```
1 # Computing the features for the generated data
2 X = np.stack(train_df.apply(lambda r: compute_all_feats(r["snake_pos"], r["snake_pos"]), axis=1))
3 y = np.stack(train_df.apple_pos.values)
4
5 X.shape, y.shape
```

Out[22]:

((903, 21), (903, 2))

In [23]:

```
1 # picked Random Forest
2 regr = RandomForestRegressor()
3 #regr = ExtraTreesRegressor()
```

To score our predictions we are going to use the strait line distance between the original apple location and the predicted one.

In [24]:

```
1 param_grid = {
2     'n_estimators': [20],
3     'max_depth': [5, 10, 20, None],
4     'min_samples_leaf': [1, 3, 9],
5     'max_features': ['auto', 0.5, 0.9]
6 }
7 # Creating our scorer
8 scorer = metrics.make_scorer(lambda y, y_pred: compute_distance(y, y_pred).mean
9
10 grid_clf = GridSearchCV(regr, param_grid, cv=gen_folds, scoring=scorer)
11 grid_clf.fit(X, y) #, sample_weight=samp_weights)
12
13 # Get best regressor
14 regr = grid_clf.best_estimator_
15
16 # Processing GridSearchCV results
17 results_df = pd.DataFrame(grid_clf.cv_results_['params'])
18 results_df["mean_test_score"] = grid_clf.cv_results_["mean_test_score"]
19 results_df.sort_values("mean_test_score", ascending=False)[:10]
```

/Users/filipe/.local/share/virtualenvs/snake_pydata-bZLAyaY7/lib/python3.7/site-packages/sklearn/model_selection/_search.py:814: Deprecation Warning: The default of the `iid` parameter will change from True to False in version 0.22 and will be removed in 0.24. This will change numeric results when test-set sizes are unequal.

DeprecationWarning)

Out[24]:

	max_depth	max_features	min_samples_leaf	n_estimators	mean_test_score
14	10.0	0.5	9	20	-152.107293
22	20.0	0.5	3	20	-152.698702
32	NaN	0.5	9	20	-153.300954
28	NaN	auto	3	20	-153.549968
4	5.0	0.5	3	20	-153.747767
26	20.0	0.9	9	20	-153.836721
31	NaN	0.5	3	20	-154.021688
3	5.0	0.5	1	20	-154.268689
23	20.0	0.5	9	20	-154.302778
8	5.0	0.9	9	20	-154.489937

In [25]:

```
1 # Trainig error and final model
2 gen_df = generate_apples(selected_df)
3 total_train_df = selected_df.append(gen_df.drop("index", axis=1), ignore_index=True)
4
5 X_total = np.stack(total_train_df.apply(lambda r: compute_all_feats(r["snake_pos", "apple_pos"]), axis=1))
6 y_total = np.stack(total_train_df.apple_pos.values)
7 samp_weights_total = total_train_df["apple_plc_score"].values*10
8
9 # Prediction and avg error
10 regr.set_params(n_estimators=100)
11 regr.fit(X_total, y_total, sample_weight=samp_weights_total)
12
```

Out[25]:

```
RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=10,
                      max_features=0.5, max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_split=None,
ne,
                      min_samples_leaf=9, min_samples_split=2,
                      min_weight_fraction_leaf=0.0, n_estimators=100,
                      n_jobs=None, oob_score=False, random_state=None,
                      verbose=0, warm_start=False)
```

In [26]:

```
1 # Training error
2 y_pred = regr.predict(X_total)
3
4 pred_dist = compute_distance(y_total, y_pred)
5
6 # We are have some overfit, once the train error is 2/3 lower than the test error
7 pred_dist.mean()
```

Out[26]:

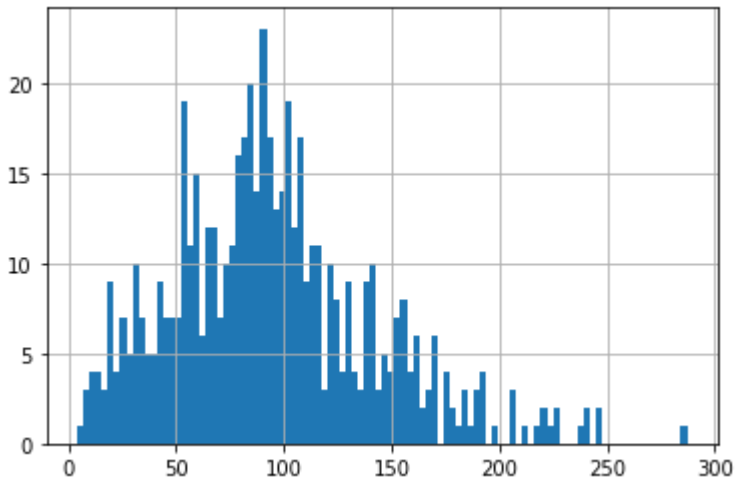
94.63433414795504

In [27]:

```
1 total_train_df["pred_apple_pos"] = np.vsplit(y_pred, y_pred.shape[0])
2 total_train_df["pred_apple_pos"] = total_train_df["pred_apple_pos"].apply(lambd
3 total_train_df["pred_dist"] = pred_dist
4 total_train_df["pred_dist"].hist(bins=100)
```

Out[27]:

<matplotlib.axes._subplots.AxesSubplot at 0x1314010b8>



In [28]:

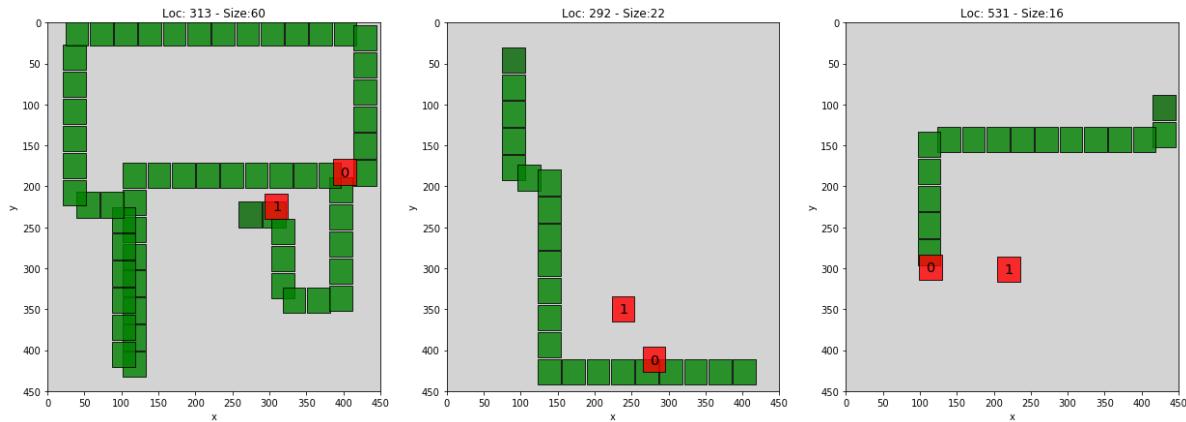
```
1 # Feature importance
2 # if scr_size is not the same, the bigger side is more important
3 features_importance_list = list(zip(feats_df.loc[:, "game_score"].columns, regr.co
4 pd.DataFrame(features_importance_list).sort_values(1, ascending=False)[:10])
```

Out[28]:

	0	1
0	norm_pos_0_x	0.115042
1	norm_pos_0_y	0.107559
12	snake_dir_D	0.102110
10	snake_dir_R	0.072882
11	snake_dir_L	0.068318
5	norm_pos_2_y	0.048683
13	snake_dir_U	0.046022
4	norm_pos_2_x	0.043108
18	avg_x	0.042093
3	norm_pos_1_y	0.040164

In [29]:

```
1 plot_snake(total_train_df.sample(3),apple_cols=["apple_pos","pred_apple_pos"])
```



In [30]:

```
1 # saving the model to be loaded in the game
2 model_name = 'regr.pkl'
3
4 with open(model_name, 'wb') as f:
5     pickle.dump(regr, f)
6 # and later you can load it
7 with open(model_name, 'rb') as f:
8     regr_ff = pickle.load(f)
9 # Making sure we load it and get the same training error
10 y_pred_ff = regr_ff.predict(X_total)
11 pred_dist_ff = compute_distance(y_total, y_pred_ff)
12 pred_dist_ff.mean()
```

Out[30]:

94.63433414795504

4.1 - Testing

To test our final prediction we shouldn't use the distance between the original apple location and the predicted one. In this cases we want to use the metrics that we defined to compare the random generator with our model, and check if our model has better average metrics than the random process.

In [31]:

```
1 test_df.head()
```

Out[31]:

	status	time_secs	score	moves_to_apple	apple_pos	snake_pos	snake_dir	time_to_apple
1036	apple	1.607	0	3	[230, 390]	[[400, 300]]	[0, 3]	1.607
1037	apple	2.263	8	1	[180, 330]	[[235, 408], [259, 417], [292, 417], [325, 417...]	[0, -3]	0.651
1038	apple	4.292	12	2	[230, 100]	[[199, 327], [232, 327], [235, 357], [235, 390...]	[-3, 0]	2.021
1039	apple	5.146	13	1	[300, 170]	[[202, 90], [169, 90], [136, 90], [136, 123], ...]	[3, 0]	0.851
1040	apple	6.243	14	1	[280, 350]	[[304, 141], [304, 108], [289, 90], [256, 90],...]	[0, 3]	1.091

In [32]:

```
1 # Computing features for the test set
2 X_test = np.stack(test_df.apply(lambda r: compute_all_feats(r["snake_pos"], r["snake_dir"], r["apple_pos"], r["score"], r["moves_to_apple"], r["time_to_apple"]), axis=1))
3 y_test = np.stack(test_df.apple_pos.values)
4 #sample_weights = test_df["apple_plc_score"].values
5 X_test.shape, y_test.shape
```

Out[32]:

```
((320, 21), (320, 2))
```

In [33]:

```
1 y_pred_test = regr.predict(X_test)
2
3 pred_dist_test = compute_distance(y_test, y_pred_test)
4
5 test_df["pred_apple_pos"] = np.vsplit(y_pred_test, y_pred_test.shape[0])
6 test_df["pred_apple_pos"] = test_df["pred_apple_pos"].apply(lambda r: np.array([r[0], r[1]]))
```

In [34]:

```
1 pred_metrics_df = compute_all_metrics(test_df, apple_pos_col_name="pred_apple_pos")
2 orig_metrics_df = compute_all_metrics(test_df, apple_pos_col_name="apple_pos")
```

In [35]:

```
1 pred_metrics_df.mean()
```

Out[35]:

```
moves_to_apple          2.387500
time_to_apple           2.277281
apple_dist              204.875670
snake_dir_to_apple_angle 122.854570
num_intersections_w_snake 0.453125
dtype: float64
```

In [36]:

```
1 orig_metrics_df.mean()
```

Out[36]:

```
moves_to_apple          2.387500
time_to_apple           2.277281
apple_dist              213.964878
snake_dir_to_apple_angle 95.087138
num_intersections_w_snake 0.309375
dtype: float64
```

5 - Create a model with your apples!

As a final challenge, I propose you to try to create a model with your own plays. For that, try to have at least 100 plays (apple catches), which, however, is still too few observations to train the model. You will have to decrease the limit of the metric's score and also increase the `n_tries` variable in the `generate_apples()` function.

Remember to change the `get_apple_location_from_model` to `False` and the `file_name` in the `snake_game/config.py` file.