Cryptocurrency Exploratory Data Analysis v0.3

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1 About the Data

1.1 Overview

All data is at the daily level, represented as a volume weighted average. Although data was available prior to 2017 for most traditional economic indicators, the same was not true for many cryptocurrencies (as many did not yet exist). Further complicating things, the crypto market has been through wild fluctuations in both 2017 and 2018, making prior periods look tame and unrepresentative of the change about to come (likely due to low volume of early adopters). For these reasons only data from 2017 forward was used for this analysis.

The sections below will constitute a data dictionary for the columns utilized in this inquiry.

1.2 Cryptocurrencies

The data we chose to use for this project includes various time-series vectors that summarize the market value of different financial instruments, index values and commodity prices. Of particular focus are a bag of cryptocurrencies that we believe are representative of the crypto market in general.

The cryptocurrencies included in this analysis are:

- BTC: Bitcoin, the first P2P digital currency by far the most valuable coin on the market
- ETH: Ethereum, a blockchain app platform for smart applications/contracts
- ETCL Ethereum Classic, focusing on fraud and smart contracts
- DASH: Dash, a coin focused on creating a digital money system
- SC: Siacoin, a decentralized storage platform (cloud) focused on under-utilized capacity
- GNT: Golem, a coin focused on under-utilized computing infrastructure for elastic computing
- LTC: Litecoin, a P2P digital currency focused on speed of transactions relative to BTC
- STR: Stellar, a coin focused on transforming the banking industry
- XEM: NEM, a coin focused on asset tracking via blockchain
- XMR: Monero, a digital currency focused on privacy
- XRP: Ripple, a digital asset focused on fast global payments

1.3 US Equity Indices

Given the importance of equity markets to the health of the overall economy, as well as the media's obsession with their movements, daily time-series of the following were included:

- SP500: SPX S&P 500 Index of large-cap US equities
- NASDAQCOM: Nasdaq Composite Index of large-cap US equities
- DJIA: Dow Jones Industrial Average of US equities
- RU2000PR: Russell 2000 Price Index of US equities

The `pandas_datareader.data` and `quandl` APIs were used to acquire this information.

1.4 Traditional Currencies

The St. Louis Federal Reserve's FRED API was accessed using the `pandas_datareader.data` API to gather currency exchange rates of the US Dollar against the Japanese Yen, the Euro, the Chinese Yuan, the Mexican Peso, and the Australian Dollar.

- DEXCHUS: Chinese Yuan to USD
- DEXJPUS: Japanese Yen to USD
- DEXUSEU: USD to European Union's Euro
- DEXMXUS: Mexican New Pesos to USD
- DEXUSAL: USD to Australian Dollar

To stay consistent, the Euro exchange rate and the Peso exchange rate are inverted to be in terms of USD like the others.

1.5 Debt Market Indicators

A ladder of bond market indicators are represented in the data in LIBOR rates at various maturities. Specifically, LIBOR is included at overnight, 1-month, 3-month and 12-month maturities. To (very crudely) represent the consumer and the corporate markets we also included indices representing high yield returns and prime corporate debt returns.

- USDONTD156N: Overnight London Interbank Offered Rate (LIBOR) based on USD
- USD1MTD156N: One Month London Interbank Offered Rate (LIBOR) based on USD
- USD3MTD156N: Three Month London Interbank Offered Rate (LIBOR) based on USD
- USD12MD156N: Twelve Month London Interbank Offered Rate (LIBOR) based on USD
- BAMLHYH0A0HYM2TRIV: ICE BofAML US High Yield Total Return Index Value
- BAMLCC0A1AAATRIV: ICE BofAML US Corp AAA Total Return Index Value

These series were also acquired from the St. Louis Fed's FRED API.

1.6 Commodity Prices

We chose to include series that represent the oil market and the gold market, two assets that are not strongly tied to the others mentioned.

- GOLDAMGBD228NLBM: Gold Fixing Price 10:30 AM (London Time) in London Bullion Market, based on USD
- DCOILWTICO: West Texas Intermediate (WTI) - Cushing Oklahoma

These series were also acquired from the St. Louis Fed's FRED API.

2 Exploratory Analysis

2.1 Methodology for Exploring Data

- Check for missing data and impute missing values and/or drop columns that are incomplete
- Characterize scale differences in the series to highlight the need for scaling
- Create a scaled version of the dataset using a standard scaler and a min-max scaler
- Enrich data with holidays and days of week to investigate whether there are any temporal patterns
- Generate a pairplots to visualize relationships between the scaled vectors
- Generate correlation matrices of (1) the series themselves and (2) the percent changes in non-scaled data

2.2 Data Cleaning & Reconciliation

In [79]:
```
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler, MinMaxScaler
import tensorflow as tf
import keras
from matplotlib import pyplot as plt
import seaborn as sns

pd.set_option('max_columns', 999)
pd.set_option('max_rows', 99999)

%matplotlib inline
```

In [67]:
```
def generate_calendar(year):
    '''
    Simple function to generate a calendar containing
    US holidays, weekdays and  holiday weeks.
    '''
    from pandas.tseries.offsets import YearEnd
    from pandas.tseries.holiday import USFederalHolidayCalendar

    start_date = pd.to_datetime('1/1/'+str(year))
    end_date = start_date + YearEnd()
    DAT = pd.date_range(str(start_date), str(end_date), freq='D')
    MO = [d.strftime('%B') for d in DAT]
    holidays = USFederalHolidayCalendar().holidays(start=start_date, end=end_date)

    cal_df = pd.DataFrame({'date':DAT, 'month':MO})
    cal_df['year'] = [format(d, '%Y') for d in DAT]
    cal_df['weekday'] = [format(d, '%A') for d in DAT]
    cal_df['is_weekday'] = cal_df.weekday.isin(['Monday','Tuesday','Wednesday','Thurs
    cal_df['is_weekday'] = cal_df['is_weekday'].astype(int)
    cal_df['is_holiday'] = cal_df['date'].isin(holidays)
    cal_df['is_holiday'] = cal_df['is_holiday'].astype(int)
```

```
        cal_df['is_holiday_week'] = cal_df.is_holiday.rolling(window=7,center=True,min_pe
        cal_df['is_holiday_week'] = cal_df['is_holiday_week'].astype(int)

        cal_df.set_index('date', inplace=True)

        return cal_df
```

```
In [2]: base_dir = 'C:/Users/pmwash/Desktop/Harvard/CS109b/Project/'
        df_eda = pd.read_csv(base_dir + 'project_data_2017_2018.csv')
```

2.2.1 Checking for Missing Data

Below we count the number of missing values for each column in the 2017-2018 dataset. It is shown that GNT, or Golem, is missing 48 of 422 expected observations due to the fact that it was not actively traded at the beginning of this time period. Given that ICOs (initial coin offerings) take a while to coordinate, missing values for GNT are imputed using backfill.

```
In [32]: count_missing = lambda df, col: {'col': col, 'missing': df[col].isnull().sum(), 'n_obs
         missing_by_col = [count_missing(df_eda, col) for col in df_eda.columns]
         pd.DataFrame(missing_by_col).set_index('col')
```

Out[32]:

col	missing	n_obs
date	0	422
DASH	0	422
ETC	0	422
ETH	0	422
GNT	48	374
LTC	0	422
SC	0	422
STR	0	422
XEM	0	422
XMR	0	422
XRP	0	422
BTC	0	422
SP500	0	422
NASDAQCOM	0	422
DJIA	0	422
RU2000PR	0	422
DEXJPUS	0	422
DEXUSEU	0	422
DEXCHUS	0	422
DEXMXUS	0	422
DEXUSAL	0	422
VIXCLS	0	422
USDONTD156N	0	422
USD1MTD156N	0	422
USD3MTD156N	0	422
USD12MD156N	0	422

```
BAMLHYH0A0HYM2TRIV        0    422
BAMLCC0A1AAATRIV          0    422
GOLDAMGBD228NLBM          0    422
DCOILWTICO                0    422
```

In [33]:
```python
df_eda['GNT'] = df_eda['GNT'].fillna(method='bfill')
count_missing(df_eda, 'GNT')
```

Out[33]:
```
{'col': 'GNT', 'missing': 0, 'n_obs': 422}
```

2.2.2 Scale Data & Save Separate Version

Below we demonstrate that there are huge differences in both the scale between the columns as well as the distributions. As is expected from the blockbuster year that many cryptos have enjoyed we see that the standard deviation of all cryptos is as large or larger than the mean. For this reason `sklearn.preprocessing.MinMaxScaler` was used to scale these columns and `sklearn.preprocessing.StandardScaler` was used to process the remainder. The minimum and maximum of `feature_range` argument of the `MinMaxScaler.fit_transform()` method was set to `(-2, 2)` in order to make the values similar to the ones produced by the `StandardScaler.fit_transform()` method. This is demonstrated by the second `pd.DataFrame.describe()` call below.

In [37]:
```python
df_eda.describe().T
```

Out[37]:

	count	mean	std	min \
DASH	422.0	315.965938	315.285763	11.444337
ETC	422.0	14.151520	10.624763	1.172033
ETH	422.0	321.980512	316.944518	8.222735
GNT	422.0	0.286022	0.224790	0.019279
LTC	422.0	69.161400	78.865807	3.708275
SC	422.0	0.009740	0.012355	0.000227
STR	422.0	0.094800	0.169957	0.001674
XEM	422.0	0.271433	0.333536	0.003243
XMR	422.0	105.726554	113.216553	10.440639
XRP	422.0	0.353831	0.512178	0.005442
BTC	422.0	4923.945371	4530.467625	788.500156
SP500	422.0	2489.489455	148.568666	2238.830000
NASDAQCOM	422.0	6366.359929	507.129439	5383.120000
DJIA	422.0	22244.410640	1788.969328	19732.400000
RU2000PR	422.0	3582.202370	178.391874	3343.270000
DEXJPUS	422.0	111.800924	2.057319	106.100000
DEXUSEU	422.0	1.143140	0.058293	1.041600
DEXCHUS	422.0	6.704823	0.179616	6.264900
DEXMXUS	422.0	18.891336	0.989531	17.477500
DEXUSAL	422.0	0.770208	0.019237	0.723000
VIXCLS	422.0	11.744526	3.335957	9.140000
USDONTD156N	422.0	1.085144	0.243293	0.680560
USD1MTD156N	422.0	1.177506	0.252199	0.763330
USD3MTD156N	422.0	1.335535	0.236321	0.997890

```
USD12MD156N          422.0     1.854391     0.191042     1.684560
BAMLHYH0A0HYM2TRIV   422.0  1234.603033    26.361849  1174.310000
BAMLCC0A1AAATRIV     422.0   615.134739    14.323038   585.160000
GOLDAMGBD228NLBM     422.0  1268.168483    42.131079  1148.650000
DCOILWTICO           422.0    52.536588     5.612550    42.480000

                             25%           50%           75%           max
DASH                   84.196241    192.375086    418.601086   1402.425173
ETC                     2.753551     14.081595     18.568618     43.423449
ETH                    49.387878    279.549049    359.964492   1363.949636
GNT                     0.088333      0.251350      0.365522      1.096991
LTC                    11.486493     45.110966     70.572352    346.905402
SC                      0.000808      0.005229      0.011616      0.064279
STR                     0.003455      0.021282      0.045196      0.785691
XEM                     0.024176      0.198715      0.269310      1.822529
XMR                    21.117876     48.058701    130.075757    425.913240
XRP                     0.033898      0.202699      0.262637      2.958787
BTC                  1243.293718   2803.574985   7246.699248  19237.154813
SP500                2376.045000   2455.525000   2584.040000   2872.870000
NASDAQCOM            5910.520000   6312.470000   6764.440000   7505.770000
DJIA                20896.610000  21730.870000  23461.045000  26616.710000
RU2000PR             3435.745000   3516.860000   3743.995000   4003.010000
DEXJPUS               110.622500    111.960000    113.235000    117.680000
DEXUSEU                 1.080050      1.162900      1.186550      1.248800
DEXCHUS                 6.599800      6.731700      6.877450      6.957500
DEXMXUS                18.158625     18.728000     19.177875     21.891000
DEXUSAL                 0.755900      0.767000      0.787275      0.810500
VIXCLS                 10.070000     10.995000     11.767500     37.320000
USDONTD156N             0.927780      1.177220      1.183645      1.448130
USD1MTD156N             0.990560      1.228890      1.249225      1.648000
USD3MTD156N             1.157610      1.310835      1.415117      1.984190
USD12MD156N             1.728440      1.775110      1.883655      2.469380
BAMLHYH0A0HYM2TRIV   1210.585000   1239.735000   1258.125000   1274.020000
BAMLCC0A1AAATRIV      602.232500    619.400000    626.590000    637.620000
GOLDAMGBD228NLBM     1241.700000   1267.800000   1290.037500   1360.250000
DCOILWTICO             48.325000     51.650000     56.210000     66.270000
```

In [48]:
```
non_norm_cols = ['DASH', 'ETC', 'ETH', 'GNT', 'LTC', 'SC', 'STR', 'XEM', 'XMR', 'XRP'
mms = MinMaxScaler(feature_range=(-2, 2))
df_eda_scaled = pd.DataFrame(mms.fit_transform(df_eda[non_norm_cols]),
                             columns=non_norm_cols,
                             index=df_eda['date'])

non_norm_cols = non_norm_cols + ['date']
norm_cols = [col for col in df_eda.columns if col not in non_norm_cols]
std = StandardScaler()
df_eda_scaled[norm_cols] = pd.DataFrame(std.fit_transform(df_eda[norm_cols]),
                                        columns=norm_cols,
```

```
                                        index=df_eda['date'])

df_eda_scaled.describe().T
```

Out[48]:

	count	mean	std	min	25%
DASH	422.0	-1.124297e+00	0.906657	-2.000000	-1.790790
ETC	422.0	-7.712141e-01	1.005861	-2.000000	-1.850276
ETH	422.0	-1.074274e+00	0.935128	-2.000000	-1.878544
GNT	422.0	-1.009966e+00	0.834323	-2.000000	-1.743701
LTC	422.0	-1.237137e+00	0.919190	-2.000000	-1.909344
SC	422.0	-1.405915e+00	0.771545	-2.000000	-1.963741
STR	422.0	-1.524879e+00	0.867109	-2.000000	-1.990915
XEM	422.0	-1.410341e+00	0.733334	-2.000000	-1.953974
XMR	422.0	-1.082626e+00	1.090003	-2.000000	-1.897204
XRP	422.0	-1.528143e+00	0.693693	-2.000000	-1.961459
BTC	422.0	-1.103361e+00	0.982287	-2.000000	-1.901393
SP500	422.0	-1.631660e-15	1.001187	-1.689165	-0.764489
NASDAQCOM	422.0	1.469072e-15	1.001187	-1.941136	-0.899930
DJIA	422.0	-1.711638e-15	1.001187	-1.405833	-0.754289
RU2000PR	422.0	-1.782145e-15	1.001187	-1.340958	-0.821961
DEXJPUS	422.0	1.381833e-14	1.001187	-2.774334	-0.573476
DEXUSEU	422.0	-3.652160e-15	1.001187	-1.743954	-1.083572
DEXCHUS	422.0	-5.419572e-16	1.001187	-2.452157	-0.585406
DEXMXUS	422.0	-3.240562e-16	1.001187	-1.430490	-0.741342
DEXUSAL	422.0	6.695539e-16	1.001187	-2.456905	-0.744643
VIXCLS	422.0	2.183614e-16	1.001187	-0.781670	-0.502558
USDONTD156N	422.0	-1.104961e-16	1.001187	-1.664920	-0.647574
USD1MTD156N	422.0	-3.367501e-17	1.001187	-1.644207	-0.742144
USD3MTD156N	422.0	-4.019954e-16	1.001187	-1.430451	-0.753788
USD12MD156N	422.0	1.778462e-16	1.001187	-0.890026	-0.660066
BAMLHYH0A0HYM2TRIV	422.0	8.248273e-15	1.001187	-2.289847	-0.912172
BAMLCC0A1AAATRIV	422.0	1.087302e-15	1.001187	-2.095248	-0.901872
GOLDAMGBD228NLBM	422.0	-6.966518e-16	1.001187	-2.840192	-0.628987
DCOILWTICO	422.0	-6.240401e-16	1.001187	-1.793931	-0.751278

	50%	75%	max
DASH	-1.479703	-0.829152	2.000000
ETC	-0.777834	-0.353041	2.000000
ETH	-1.199466	-0.962205	2.000000
GNT	-1.138653	-0.714897	2.000000
LTC	-1.517447	-1.220692	2.000000
SC	-1.687661	-1.288804	2.000000
STR	-1.899960	-1.777956	2.000000
XEM	-1.570222	-1.415008	2.000000
XMR	-1.637829	-0.848202	2.000000
XRP	-1.732836	-1.651656	2.000000
BTC	-1.563096	-0.599746	2.000000
SP500	-0.228883	0.637165	2.583557

```
NASDAQCOM          -0.106391  0.785899  2.249450
DJIA               -0.287400  0.680883  2.446934
RU2000PR           -0.366720  0.908027  2.361694
DEXJPUS             0.077414  0.697888  2.861031
DEXUSEU             0.339383  0.745573  1.814722
DEXCHUS             0.149811  0.962230  1.408432
DEXMXUS            -0.165260  0.289915  3.034999
DEXUSAL            -0.166949  0.888252  2.096984
VIXCLS             -0.224948  0.006895  7.675707
USDONTD156N         0.378907  0.405346  1.493740
USD1MTD156N         0.203984  0.284710  1.867777
USD3MTD156N        -0.104642  0.337157  2.748064
USD12MD156N        -0.415485  0.153361  3.222942
BAMLHYH0A0HYM2TRIV  0.194905  0.893332  1.497002
BAMLCC0A1AAATRIV    0.298144  0.800728  1.571730
GOLDAMGBD228NLBM   -0.008756  0.519687  2.188190
DCOILWTICO         -0.158153  0.655277  2.449816
```

2.2.3 Merge Calendar Information

The self-authored function `generate_calendar` generates calendar features for all days in a given year. This function utilizes pandas' `pd.tseries.offsets.YearEnd` and `pd.tseries.holiday.USFederalHolidayCalendar` classes to get information on US holidays.

In [68]:
```
yrz = [2017, 2018]
cal_df = pd.DataFrame()
for yr in yrz:
    cal_df = cal_df.append(generate_calendar(year=yr))

cal_df.head()
```

Out[68]:
```
              month  year    weekday  is_weekday  is_holiday  is_holiday_week
date
2017-01-01  January  2017     Sunday           0           0                1
2017-01-02  January  2017     Monday           1           1                1
2017-01-03  January  2017    Tuesday           1           0                1
2017-01-04  January  2017  Wednesday           1           0                1
2017-01-05  January  2017   Thursday           1           0                1
```

In [69]:
```
df_eda_scaled = df_eda_scaled.join(cal_df)
df_eda_scaled.head()
```

Out[69]:
```
                DASH       ETC       ETH       GNT       LTC        SC  \
date
2017-01-01 -2.000000 -1.975785 -1.999555 -1.921301 -1.991252 -2.000000
2017-01-02 -1.999326 -1.977608 -2.000000 -1.921301 -1.989797 -1.999620
2017-01-03 -1.996616 -1.969486 -1.996865 -1.921301 -1.990180 -1.999517
2017-01-04 -1.988252 -1.957044 -1.992946 -1.921301 -1.990177 -1.997820
2017-01-05 -1.991918 -1.961096 -1.994650 -1.921301 -1.992550 -1.997886
```

```
                 STR       XEM       XMR       XRP       BTC     SP500  \
date
2017-01-01 -1.995731 -1.999501 -1.969275 -1.998602 -1.956631 -1.689165
2017-01-02 -1.996010 -1.999743 -1.953251 -1.998862 -1.950898 -1.689165
2017-01-03 -1.995869 -1.999533 -1.945859 -1.998746 -1.949335 -1.561126
2017-01-04 -1.995161 -1.999537 -1.935472 -1.998506 -1.934031 -1.474060
2017-01-05 -1.995881 -1.999884 -1.945725 -1.999425 -1.953132 -1.485853

            NASDAQCOM      DJIA  RU2000PR   DEXJPUS   DEXUSEU   DEXCHUS  \
date
2017-01-01  -1.941136 -1.388932 -1.175171  2.423049 -1.510373  1.327609
2017-01-02  -1.941136 -1.388932 -1.175171  2.423049 -1.510373  1.327609
2017-01-03  -1.850400 -1.322245 -1.058547  2.861031 -1.743954  1.408432
2017-01-04  -1.755795 -1.288442 -0.745213  2.715037 -1.640903  1.267409
2017-01-05  -1.734197 -1.312434 -0.968638  1.780676 -1.431367  1.015462

             DEXMXUS   DEXUSAL    VIXCLS  USDONTD156N  USD1MTD156N  \
date
2017-01-01  1.745992 -2.456905  0.688917    -1.617390    -1.611099
2017-01-02  1.745992 -2.456905  0.688917    -1.617390    -1.611099
2017-01-03  2.038396 -2.451701  0.331775    -1.603686    -1.604509
2017-01-04  2.523545 -2.248727  0.031655    -1.624262    -1.635354
2017-01-05  2.533157 -1.915643 -0.022367    -1.616937    -1.635354

            USD3MTD156N  USD12MD156N  BAMLHYH0A0HYM2TRIV  BAMLCC0A1AAATRIV  \
date
2017-01-01    -1.430451    -0.884209           -2.289847         -1.605246
2017-01-02    -1.430451    -0.884209           -2.289847         -1.605246
2017-01-03    -1.426935    -0.866758           -2.169834         -1.573791
2017-01-04    -1.399863    -0.866758           -2.006526         -1.525559
2017-01-05    -1.382197    -0.866758           -1.903984         -1.204716

            GOLDAMGBD228NLBM  DCOILWTICO    month  year    weekday  \
date
2017-01-01         -2.591862    0.216453  January  2017     Sunday
2017-01-02         -2.591862    0.216453  January  2017     Monday
2017-01-03         -2.840192   -0.031500  January  2017    Tuesday
2017-01-04         -2.430269    0.129045  January  2017  Wednesday
2017-01-05         -2.260359    0.220021  January  2017   Thursday

            is_weekday  is_holiday  is_holiday_week
date
2017-01-01           0           0                1
2017-01-02           1           1                1
2017-01-03           1           0                1
2017-01-04           1           0                1
2017-01-05           1           0                1
```

2.2.4 Pairplots of Features

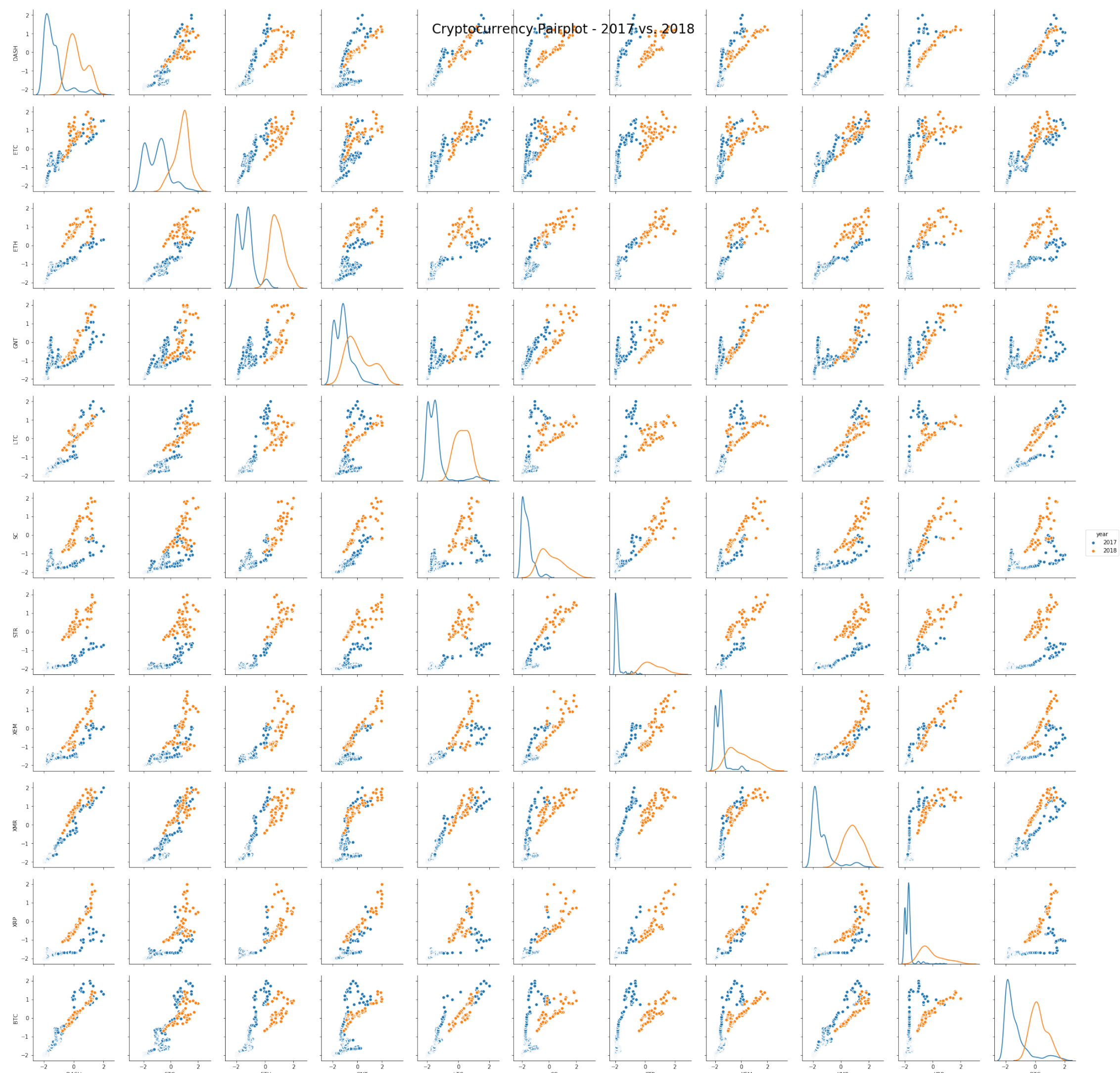
Below we investigate the correlations between the scaled features. Two pairplots are created: one for the cryptocurrencies and one for the more traditional financial assets. To investigate the existence of a bubble in either market over time, as well as for visual purposes, the year is highlighted in both pairplots.

In [74]:
```
non_norm_cols.pop()
cols_to_plot = non_norm_cols + norm_cols
cols_to_plot
```

Out[74]:
```
'date'
```

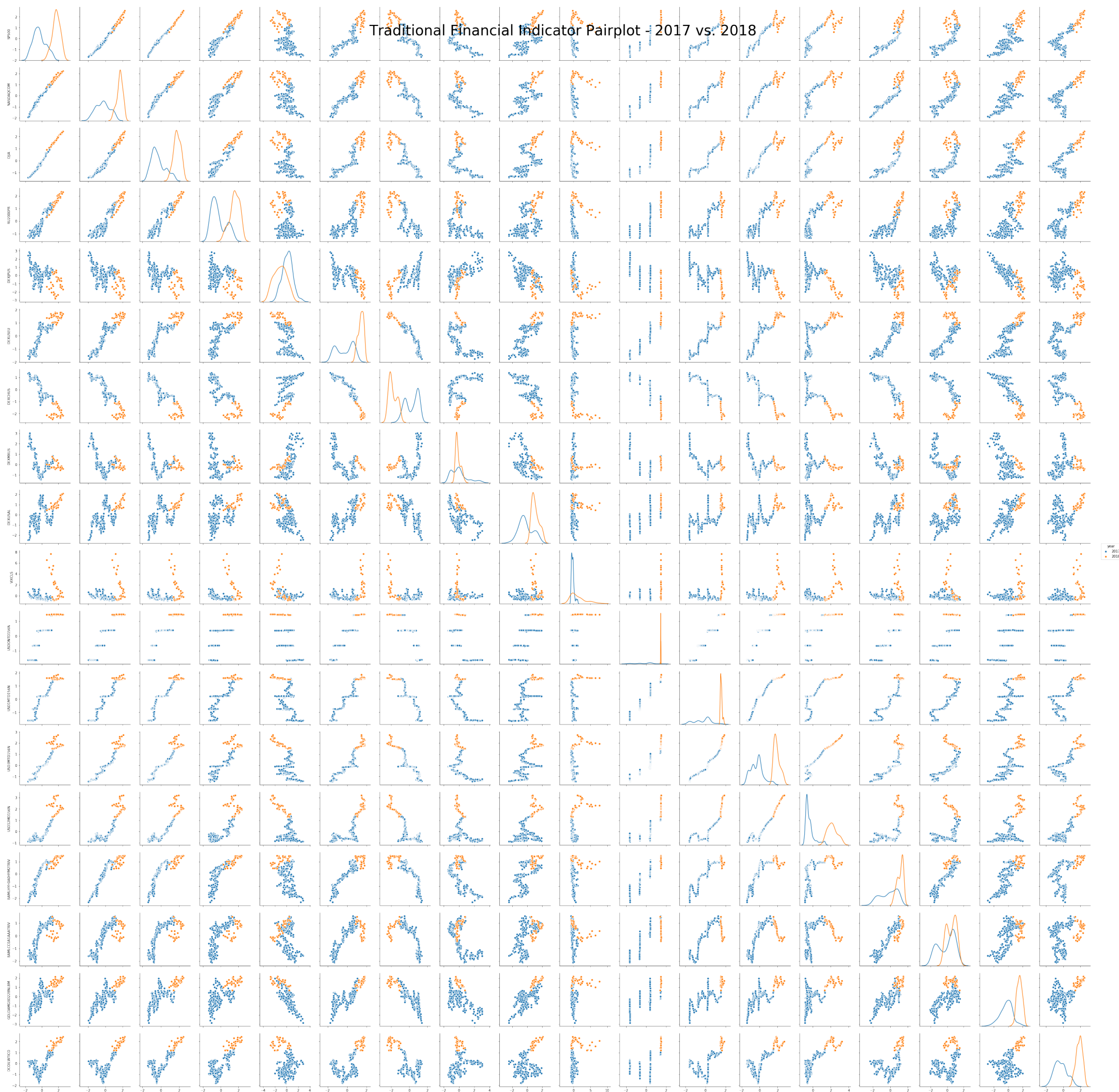
In [91]:
```
sns.pairplot(df_eda_scaled, vars=non_norm_cols, hue='year', diag_kind='kde')
plt.suptitle('Cryptocurrency Pairplot - 2017 vs. 2018', size=24)
```

Out[91]:
```
Text(0.5,0.98,'Cryptocurrency Pairplot - 2017 vs. 2018')
```



In [93]:
```
sns.pairplot(df_eda_scaled, vars=norm_cols, hue='year', diag_kind='kde')
plt.suptitle('Traditional Financial Indicator Pairplot - 2017 vs. 2018', size=42)
```

Out[93]:
```
Text(0.5,0.98,'Traditional Financial Indicator Pairplot - 2017 vs. 2018')
```



It is interesting to note that by grouping the data by year (2017 and 2018) we see strong separation in both the scatterplots and the kernel density plots on the diagonals. This could be indicative of a bubble, but is definitely indicative that the markets have been moving over time.

The cryptocurrency pairlot shows strong positive correlation between the various coins. This was somewhat expected given the market movements that have transpired this year.

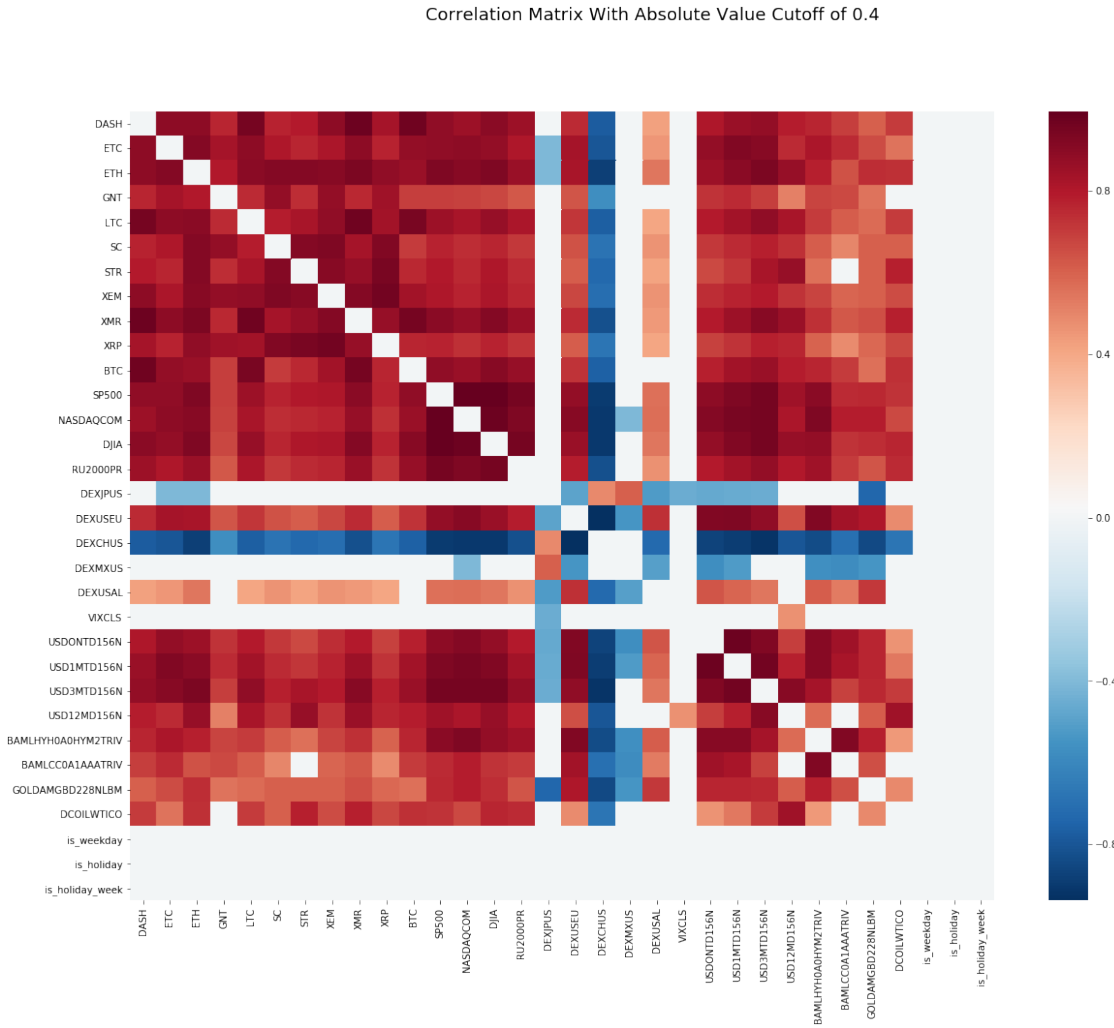
As was somewhat expected at the outset (based on the shear number of features involved in this analysis) these plots are somewhat difficult to read and interpret. This was the reason behind using correlation matrices below. However it is still interesting to note some of the very interesting patterns that exist in the financial datasets -- the scatterplots show a strange non-linearity in some of the pairs. This may be some complex economic interaction, an effect of scaling the data, or simply some other phenomenon that has not been considered. This does, however, bring up the problem of collinearity in the X variables.

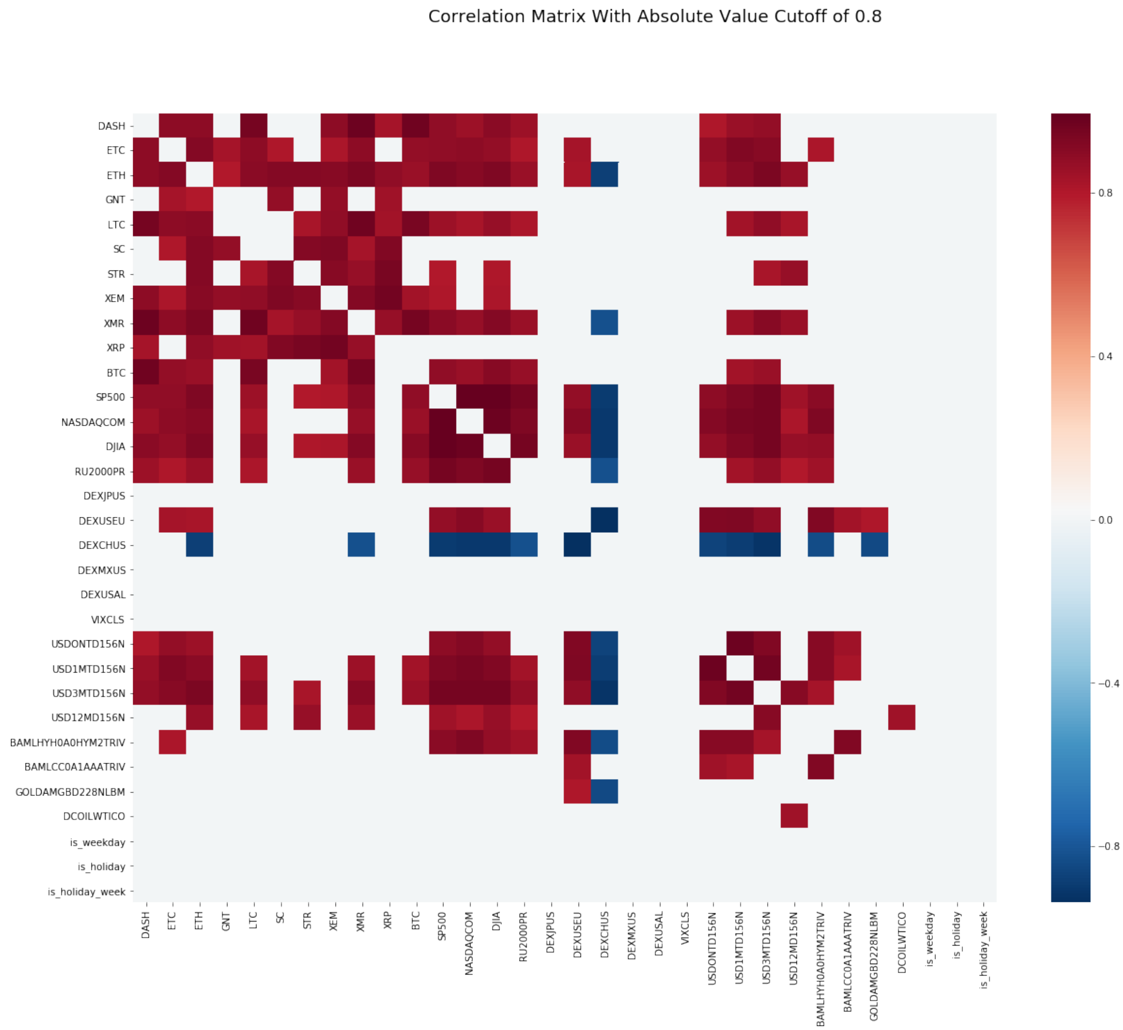
2.2.5 Heatmaps of Scaled Data Correlation Matrix at Various Cutoffs

The function `correlation_heatmap` below produces a pearson correlation matrix between the features, sets the diagonal to zero (for visual purposes), then mutes all correlation values that are below a specified `cutoff` argument. This cutoff is helpful in filtering out the noise.

```
In [142]: def correlation_heatmap(df, cutoff=None, title=''):
              df_corr = df.corr('pearson')
              np.fill_diagonal(df_corr.values, 0)
              if cutoff != None:
                  for col in df_corr.columns:
                      df_corr.loc[df_corr[col].abs() <= cutoff, col] = 0
              fig, ax = plt.subplots(figsize=(20, 15))
              sns.heatmap(df_corr, ax=ax, cmap='RdBu_r')
              plt.suptitle(title, size=18)
              plt.show()
              return df_corr


          cutoffs = [.4, .8]
          for cutoff in cutoffs:
              _ = correlation_heatmap(df_eda_scaled, cutoff, 'Correlation Matrix With Absolute
```


Correlation Matrix With Absolute Value Cutoff of 0.4
DASH
ETC
ETH
GNT
LTC
SC
STR
XEM
XMR
XRP
BTC
SP500
NASDAQCOM
DJIA
RU2000PR
DEXJPUS
DEXUSEU
DEXCHUS
DEXMXUS
DEXUSAL
VIXCLS
USDONTD156N
USD1MTD156N
USD3MTD156N
USD12MD156N
BAMLHYH0A0HYM2TRIV
BAMLCC0A1AAATRIV
GOLDAMGBD228NLBM
DCOILWTICO
is_weekday
is_holiday
is_holiday_week
0.8
0.4
0.0
−0.4
−0.8

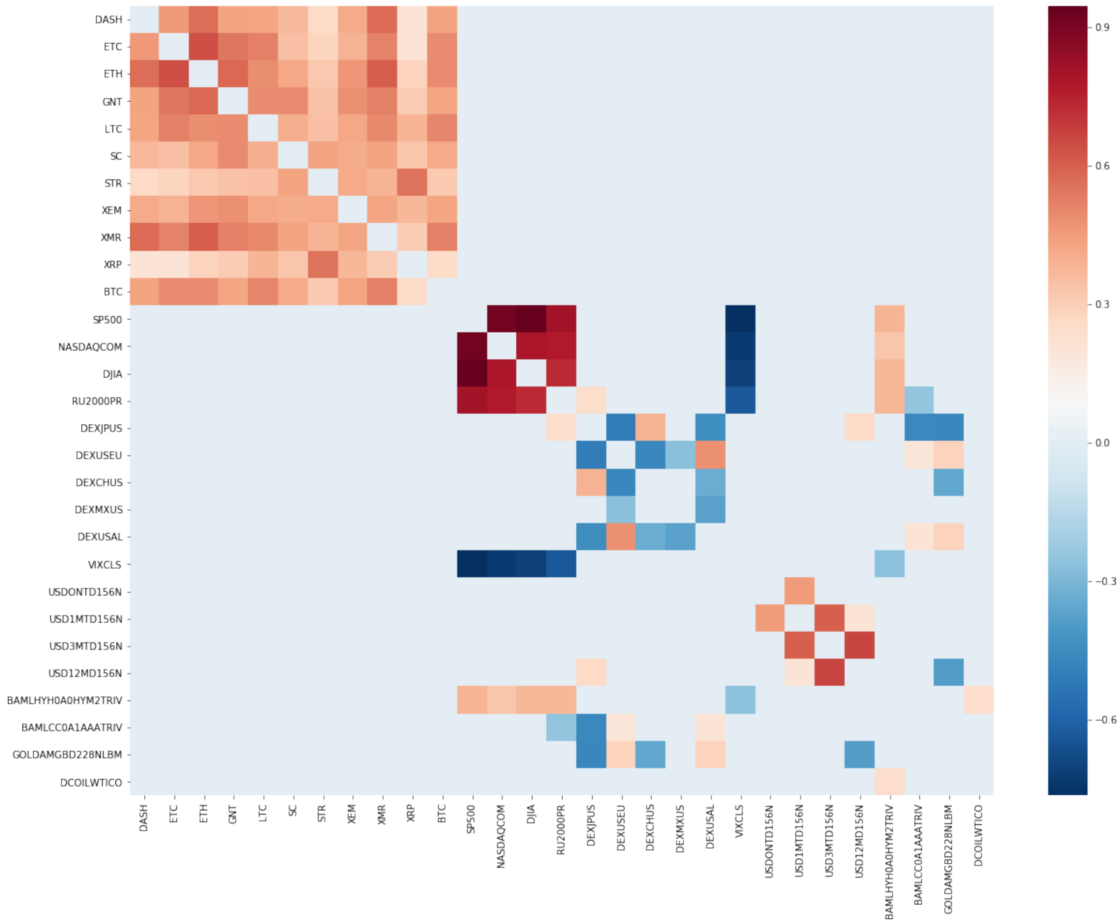


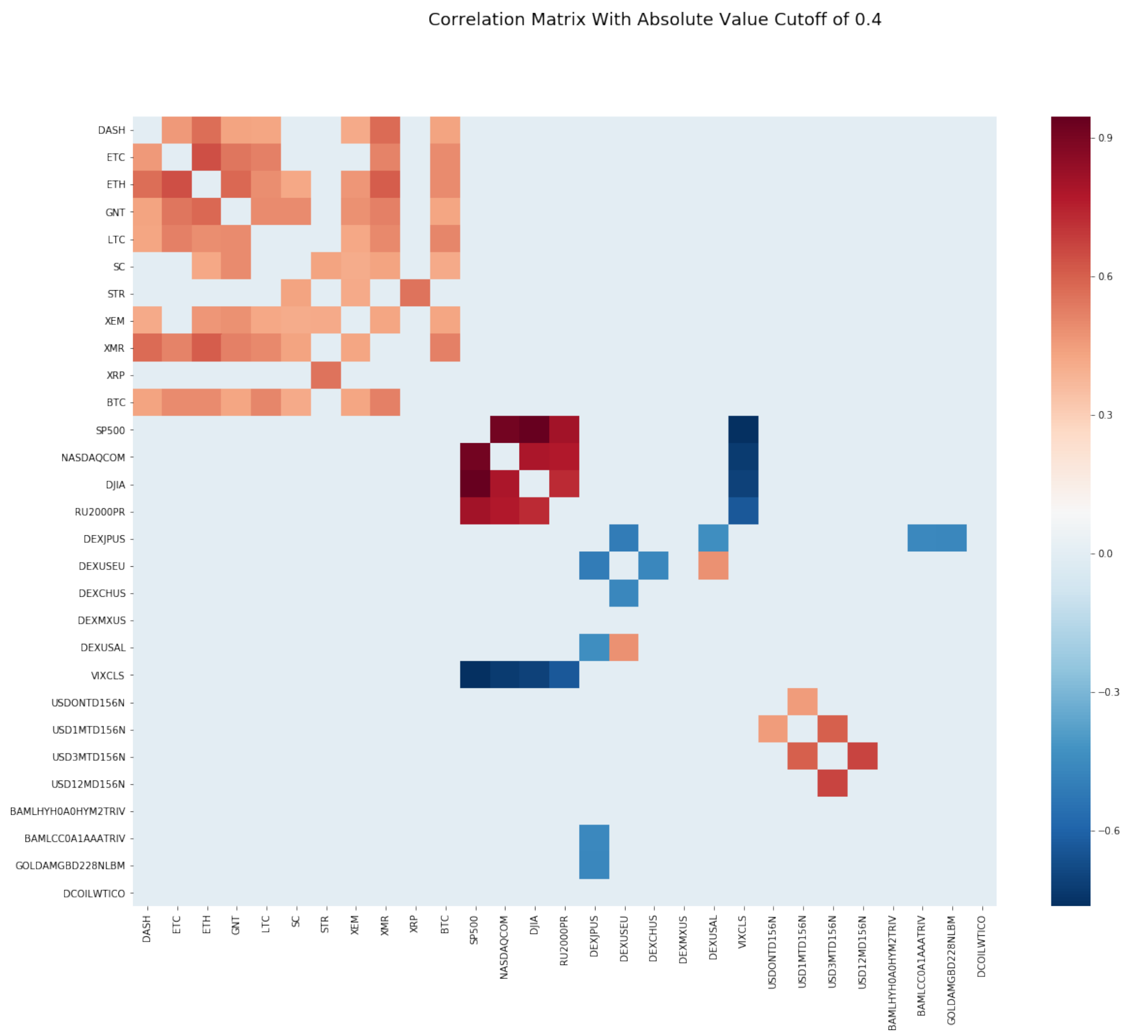
2.2.6 Heatmaps of Percent Changes in Original Data Using Correlation Matrices at Various Cutoffs

The same function used above is also used to explore the percent changes of the features in `tseries_cols`. This is to get a feel for which series move together as a function of magnitude and time.

```
In [141]: tseries_cols = non_norm_cols + norm_cols
          df_eda_pct_change = df_eda[tseries_cols].pct_change()
          cutoffs = [.2, .4]
          for cutoff in cutoffs:
              _ = correlation_heatmap(df_eda_pct_change, cutoff, 'Correlation Matrix With Abso
```

Correlation Matrix With Absolute Value Cutoff of 0.2





Consistent with the literature we came across on the crypto-markets we observe that the various coins are strongly positively correlated with one another, both in their time-series form and in their percent-change form. Perhaps also unsurprisingly we observe the same phenomena in the various equity markets (which also tend to move together through time).

The correlations between the different debt markets are expected since the longer maturity instruments are a function of the shorter maturity contracts.

It is also noteworthy that the `VIXCLS` percent change correlation has a strong negative correlation with all of the equity markets, reflecting the tumultuous couple years since the 2016 US election. However the VIX does not show strong signal in the scaled data correlation matrix representation done first, shown by the fact that most of the VIX row/column is muted by the `cutoff` parameter. The only un-muted cells are between the VIX and the USD-Yen (strong negative) and the VIX and the US 12 month rate.

3 Revised Project Question

Given the messiness inherent in cryptocurrency markets, as well as all financial markets, we hope to simplify the analysis by reviewing both regression and classification techniques. We hypothesize that a classification model will perform better than a regression model, and is likely to lead to better outcomes in a real-world scenario. We also plan to simplify the world by taking the magnitude of investment out of any model that may be produced so that our recommendations are simply either **buy, sell or hold**.

As of 4/19/2018 our working plan is the following:

- Decide on what our outcome variables will be for both regression and classification
- Set two baseline models: (1) Random Forest and (2) simply predicting the previouo day's value
- Test recurrent network flavor, either LSTM or GRU, to see if they have any efficacy whatsoever
- Update data for new outcome variables: whether the outcome (1) gained by X%, (2) fell by X%, or (3) did neither
- Train an autoencoder to extract features and reduce collinearity in the data
- Test deep feed forward network as a classification of the above new targets
- Methodically track hyperparameters in spreadsheet as we try them to explore hyperparameter space in a disciplined manner
- Backtest our best models and evaluate findings