

Spatial Temporal Koopman decomposition for crypto-valuation prediction

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Abstract

A prediction analysis applied on a dynamical system such as crypto currency using the principles of spatio temporal koopman decomposition for a higher dimensions. We go through the basic theory with our data-driven approach using higher order dynamic mode decomposition taking certain dimensions from sentiment analysis from news and tweets generated on the topic "Bitcoin" and "Dogecoin" which are famous crypto-currency in circulation in the economy.

Introduction on Mathematical Concepts used:

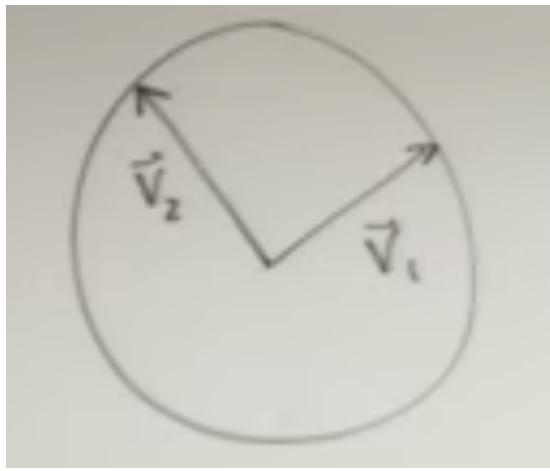
Singular Value Decomposition

Consider $\vec{x} = \begin{pmatrix} 1 \\ 3 \end{pmatrix}$ and $A = \begin{pmatrix} 2 & 1 \\ -1 & 1 \end{pmatrix}$, then $\vec{y} = A\vec{x} = \begin{pmatrix} 2 & 1 \\ -1 & 1 \end{pmatrix} \begin{pmatrix} 1 \\ 3 \end{pmatrix} = \begin{pmatrix} 5 \\ 2 \end{pmatrix}$. \vec{y} is basically a rotated and stretched form of \vec{x} .

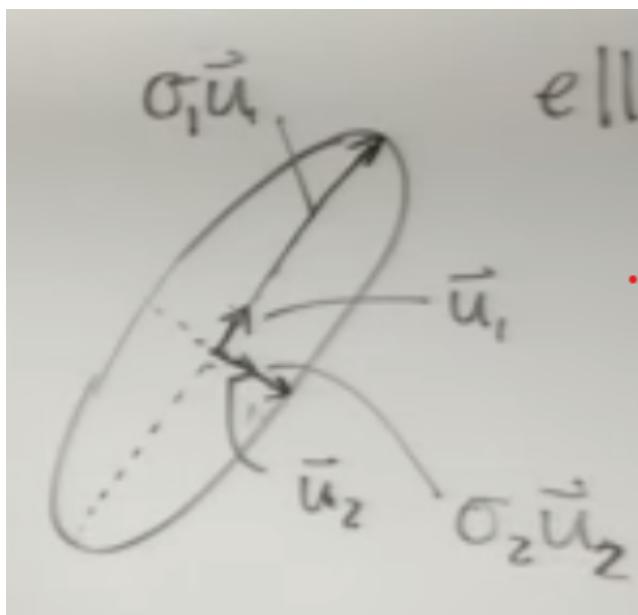
Now $\begin{pmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{pmatrix}$ is a rotation matrix and $\begin{pmatrix} \alpha & 0 \\ 0 & \alpha \end{pmatrix}$, where α is a *positive real number*, is a stretching/translational matrix and A is composed of these two.

Now consider a circle in 2-dimensions with its orthogonal direction co-ordinates being v_1 and v_2 .

(in n -dimensions it would be v_1, v_2, \dots, v_n)



When an $A_{m \times n}$, is operated on this circle it becomes an ellipse (*it is rotated and then stretched*):



where u_1 and u_2 are the unit vectors in those directions and σ_1 and σ_2 are the distances along the unit vectors.

$\therefore v_1, v_2, \dots, v_n$ vector space gets transformed to u_1, u_2, \dots, u_n with $\sigma_1, \sigma_2, \dots, \sigma_n$ as stretching factors, when multiplied by A . The $\sigma_1, \sigma_2, \dots, \sigma_n$ are known as the **singular values**.

Therefore in vector terms: $A \vec{v}_j = \sigma_j \vec{u}_j$, $j = 1, 2, \dots, n$.

$$\left[A \right]_{m \times n} \begin{bmatrix} \vec{v}_1 & \vec{v}_2 & \dots & \vec{v}_n \end{bmatrix}_{n \times n} = \begin{bmatrix} \vec{u}_1 & \vec{u}_2 & \dots & \vec{u}_n \end{bmatrix}_{m \times n} \begin{bmatrix} \sigma_1 & & 0 \\ & \sigma_2 & \\ 0 & & \ddots & \sigma_n \end{bmatrix}_{n \times n}$$

$$\therefore AV = \hat{U}\hat{\Sigma}$$

from V and \hat{U} it could be seen that these are unitary transformation matrices and orthogonal too. Thus

$V^{-1} = V^*$ and $\hat{U}^{-1} = \hat{U}^*$. On right multiplication with V^{-1} we get

$A = \hat{U}\hat{\Sigma}V^*$ —> reduced SVD of A.

Since \hat{U} is of size $m \times n$, $m-n$ extra silent columns can be added to make it $m \times m$ and the $\hat{\Sigma}$ can be stretched with $m-n$ rows of 0's to make its size $m \times n$.

$\therefore A_{m \times n} = U_{m \times m}\Sigma_{m \times n}V_{n \times n}^*$ —> **Singular Value Decomposition** of A, where

$(\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_n \geq 0)$.

To get the U , Σ and V matrices we follow these steps:

$$A^T A = (U \Sigma V^*)^T (U \Sigma V^*)$$

$$A^T A = V \Sigma U^* U \Sigma V^*$$

$$A^T A = V \Sigma^2 V^*$$

$$A^T A V = (V \Sigma^2 V^*) V$$

$$\therefore A^T A V = \Sigma^2 V$$

This is the same as $Av = \lambda v$, thus by solving this eigen-value problem we would get the Σ^2 and V values.

$$A A^T = (U \Sigma V^*)(U \Sigma V^*)^T$$

$$A A^T = U \Sigma V^* V \Sigma U^*$$

$$A A^T = U \Sigma^2 U^*$$

$$A A^T U = (U \Sigma^2 U^*) U$$

$$\therefore A A^T U = \Sigma^2 U$$

```
clear all;close all;clc;
A = randi(10,3);
[u1, s1, v1] = svd(A);
[v2,ss21] = eig(A'*A);
[u2, ss12] = eig(A*A');
s2 = sqrt(ss12);
u1
```

```
u1 = 3x3
-0.6252    0.5269    0.5758
-0.4124    0.4033   -0.8168
-0.6626   -0.7481   -0.0349
```

```
u2
```

```
u2 = 3x3
 0.5758    0.5269    0.6252
 -0.8168    0.4033    0.4124
 -0.0349   -0.7481    0.6626
```

```
disp("*****")
```

```
*****
```

```
s1
```

```
s1 = 3x3
12.2010      0      0
  0    7.1490      0
  0      0    5.1018
```

```
s2
```

```
s2 = 3x3
  5.1018      0      0
  0    7.1490      0
  0      0    12.2010
```

```
disp("*****")
```

```
*****
```

```
v1
```

```
v1 = 3x3
-0.5502    0.4804   -0.6830
-0.6066    0.3321    0.7223
-0.5738   -0.8117   -0.1088
```

```
v2
```

```
v2 = 3x3
  0.6830    0.4804    0.5502
  -0.7223   0.3321    0.6066
  0.1088   -0.8117   0.5738
```

$A^T A$ and AA^T are hermitian matrices thus the eigen values are **always positive, real and distinct**.

Dynamic Mode Decomposition

A method to reduce the dimensionality of an algorithm. It is seen as an application extracted from the idea of Koopman Spectral analysis.

We consider this method to be more data-driven and on futher explain DMD for higher order dimension non-linear systems.

Basic idea

Non-linear to best linear approximation,

$$\frac{d\underline{x}}{dt} = f(\underline{x}, t, \mu) \rightarrow \frac{d\underline{x}}{dt} = A\underline{x}$$

We measure x for any time-point,

$$x_j = \underline{x}(t_j)$$

So,

$$X = [x_1 \ x_2 \ x_3 \ \dots \dots \ x_{m-1}]$$

$$X' = [x_2 \ x_3 \ x_4 \ \dots \dots \ x_m]$$

Our objective is to find the best matrix that takes X to X' $X' = AX$

Here matrix \mathbf{A} is seen as an operator that takes us Δt times into the future from X to X'

Now from the equation we can calculate X by multiplying its respective pseudo inverse on both sides,

Final equation $\rightarrow A = X'X^+$

This equation is the exact depiction of working of DMD but cannot be practically implemented in data-driven cases. Given our X has N columns multiplied by N rows of its pseudo inverse we get $N \times N$ matrix \mathbf{A} which is computationally not feasible. So we can define it as an algorithm.

Step 1: Decompose X using SVD

$$X = U\Sigma V^*$$

We reduce the rank using rank truncation and use that as the subspace for building the model

$$X = U_r \Sigma_r V_r^*$$

Step 2:

$$\begin{aligned} A &= X'X^+ \\ &= X'V\Sigma^{-1}U^* \end{aligned}$$

We will be working with a similarity transform of A denoted as \tilde{A}

$$\tilde{A} = U^*AU$$

$$\tilde{A}_{\text{rxr}} = U^*X'V\Sigma^{-1}$$

Step 3:

we do an eigenvalue decomposition

$$\hat{A}W = W\Lambda$$

where W is [eigenvectors] and Λ is $\begin{bmatrix} \lambda_1 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & \lambda_r \end{bmatrix}$

Step 4:

Bring it back to the original higher rank

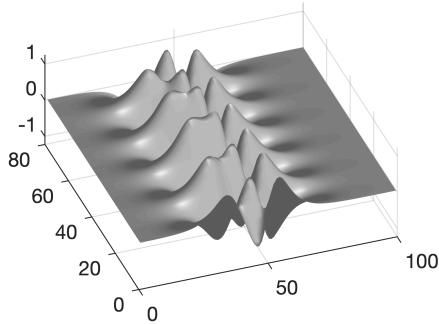
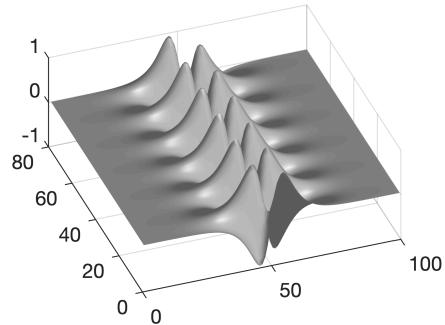
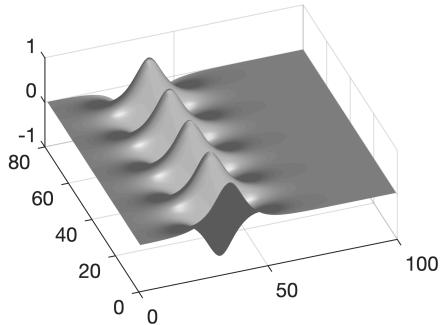
$$\phi = X' V \Sigma^{-1} W \longrightarrow \text{DMD modes}$$

$$X(t) = \phi e^{\Omega t} b = \sum_{k=1}^r \phi_k e^{w_k t} b_k \quad \text{where} \quad b = \frac{\phi}{x(0)}$$

```
x=linspace(-10,10,100);
t=linspace(0,4*pi,80); dt=t(2)-t(1);
[X,T]=meshgrid(x,t);
```

```
f1=sech(X+3).*(1*exp(i*2.3*T));
f2=(sech(X).*tanh(X)).*(2*exp(i*2.8*T));
f=f1+f2;

subplot(2,2,1), surf1(real(f1)), shading interp, colormap(gray), view(-20,60)
subplot(2,2,2), surf1(real(f2)), shading interp, colormap(gray), view(-20,60)
subplot(2,2,3), surf1(real(f)), shading interp, colormap(gray), view(-20,60)
```



```
[u,s,v]=svd(f');

figure(2)
subplot(4,3,1), plot(diag(s)/sum(diag(s)), 'ko', 'Linewidth', [2])
subplot(4,1,2), plot(t,v(:,1)/max(v(:,1)), t,v(:,2)/max(v(:,2)), 'Linewidth', [2])
```

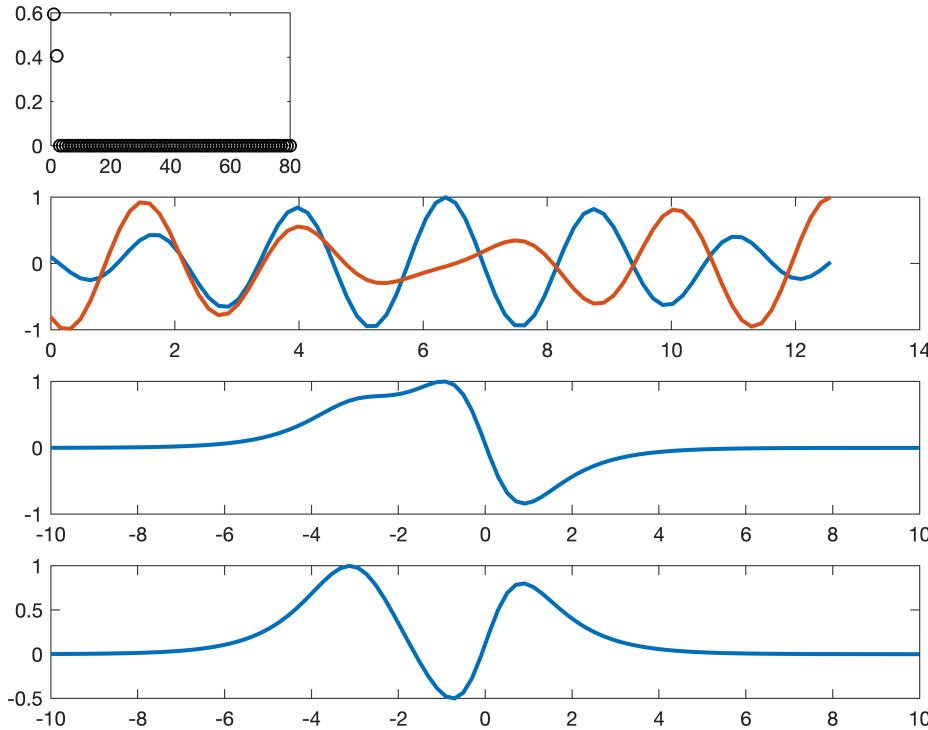
Warning: Imaginary parts of complex X and/or Y arguments ignored.

```
subplot(4,1,3), plot(x,u(:,1)/max(u(:,1)), 'Linewidth',[2])
```

Warning: Imaginary parts of complex X and/or Y arguments ignored.

```
subplot(4,1,4), plot(x,u(:,2)/max(u(:,2)), 'Linewidth',[2])
```

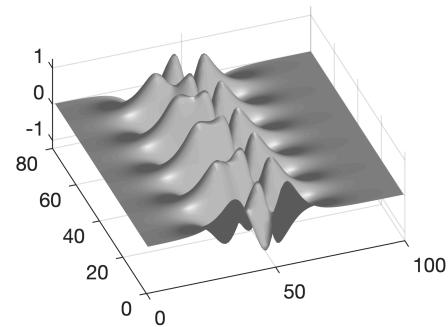
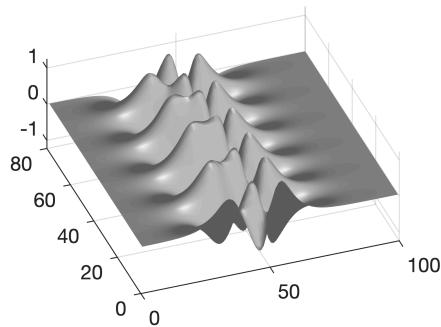
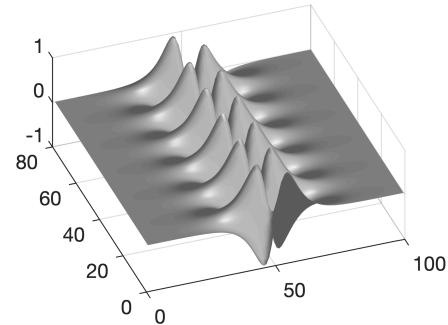
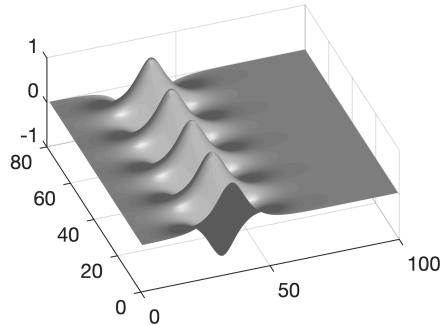
Warning: Imaginary parts of complex X and/or Y arguments ignored.



```
X = f.'; X1 = X(:,1:end-1); X2 = X(:,2:end);  
r=2;
```

```
[U2,Sigma2,V2] = svd(X1, 'econ'); U=U2(:,1:r); Sigma=Sigma2(1:r,1:r); V=V2(:,1:r);  
Atilde = U'*X2*V/Sigma;  
[W,D] = eig(Atilde);  
Phi = X2*V/Sigma*W;  
  
mu = diag(D);  
omega = log(mu)/dt;  
  
u0=f(1,:).';  
y0 = Phi\u0; % pseudo-inverse initial conditions  
u_modes = zeros(r,length(t));  
for iter = 1:length(t)  
    u_modes(:,iter) =(y0.*exp(omega*t(iter)));  
end  
u_dmd = Phi*u_modes;
```

```
figure(1)
subplot(2,2,4)
surf(real(u_dmd.')), shading interp, colormap(gray), view(-20,60)
```



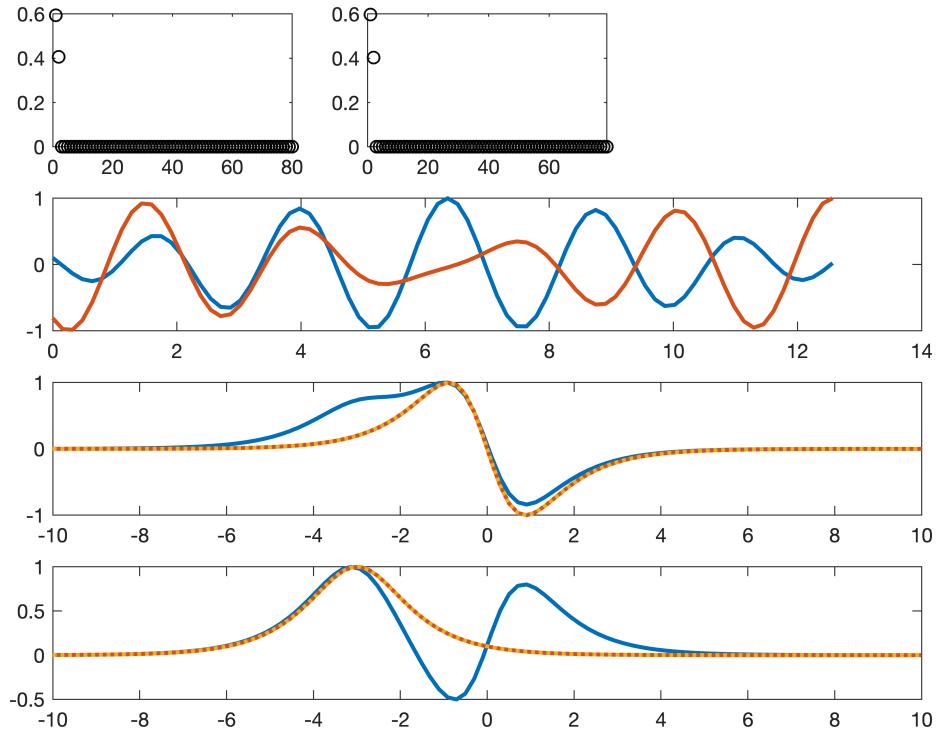
```
figure(2),
subplot(4,3,2), plot(diag(Sigma2)/sum(diag(Sigma2)), 'ko', 'Linewidth',[2])
subplot(4,1,3), hold on, plot(x,-Phi(:,1)/max(Phi(:,1)), 'Linewidth',[2])
```

Warning: Imaginary parts of complex X and/or Y arguments ignored.

```
subplot(4,1,4), hold on, plot(x,Phi(:,2)/max(Phi(:,2)), 'Linewidth',[2])
```

Warning: Imaginary parts of complex X and/or Y arguments ignored.

```
subplot(4,1,3), plot(x,-sech(x).*tanh(x)/max(sech(x).*tanh(x)), ':', 'Linewidth',[2])
subplot(4,1,4), plot(x,sech(x+3)/max(sech(x+3)), ':', 'Linewidth',[2])
```



Higher Order Dynamic Mode Decomposition

Lets assume a dynammic system given by the vector state variable $v(t)$, of size n , we consider a set of K snapshots at equispaced values of t

$$v_k \equiv v(t_k)$$

where $t_k = t_1 + (k - 1) \cdot \Delta t$, for $k = 1, \dots, K$

Assuming the dynamical system is infinite-dimensional, the finite- dimensional state vector V generally results from spatial discretization. The snapshots

are organized in a snapshot matrix (whose columns are the snapshots), as

$$V^k = [v_1 \ v_2 \ \dots \ v_k]$$

Metrics: *relative root mean square (RMS) error*, defined as

$$\text{error} = \sqrt{\frac{\sum_{k=1}^K \|v_k^{\text{approx}} - v_k\|_2^2}{\sum_{k=1}^K \|v_k\|_2^2}}$$

Algorithm:

SVD :

For dimensionality reduction, truncated SVD is applied to V_1^k , which yields,

$$V_1^k \approx P\Sigma Q^T \equiv P\hat{T}_1^K \quad (\text{or } v_k \equiv P\hat{t}_k)$$

where $\hat{T}_1 = \Sigma Q^T$

where the matrix \hat{T}_1^K is known as the dimension-reduced snapshot matrix and their columns, the *dimension-reduced snapshots*, \hat{t}_k .

DMDd:

For ordinary DMD, we consider the Koopman Assumption which can be formulated as,

$$\hat{t}_{k+1} = \hat{R}^t \cdot \hat{t}_k$$

Where the $M \times M$ matrix \hat{R}^t is computed from dimension-reduced snapshots via pseudoinverse.

Reduced Snapshots can be represented by,

$$\hat{t}_{k+d} \approx \hat{R}_1 \hat{t}_{k+d-1} + \hat{R}_2 \hat{t}_{k+d-2} + \dots + \hat{R}_k \hat{t}_k$$

The enlarged snapshots can be represented by,

$$\tilde{t}_k \equiv \begin{bmatrix} \hat{t}_k \\ \hat{t}_{k+1} \\ \vdots \\ \hat{t}_{k+d-2} \\ \hat{t}_{k+d-1} \end{bmatrix}$$

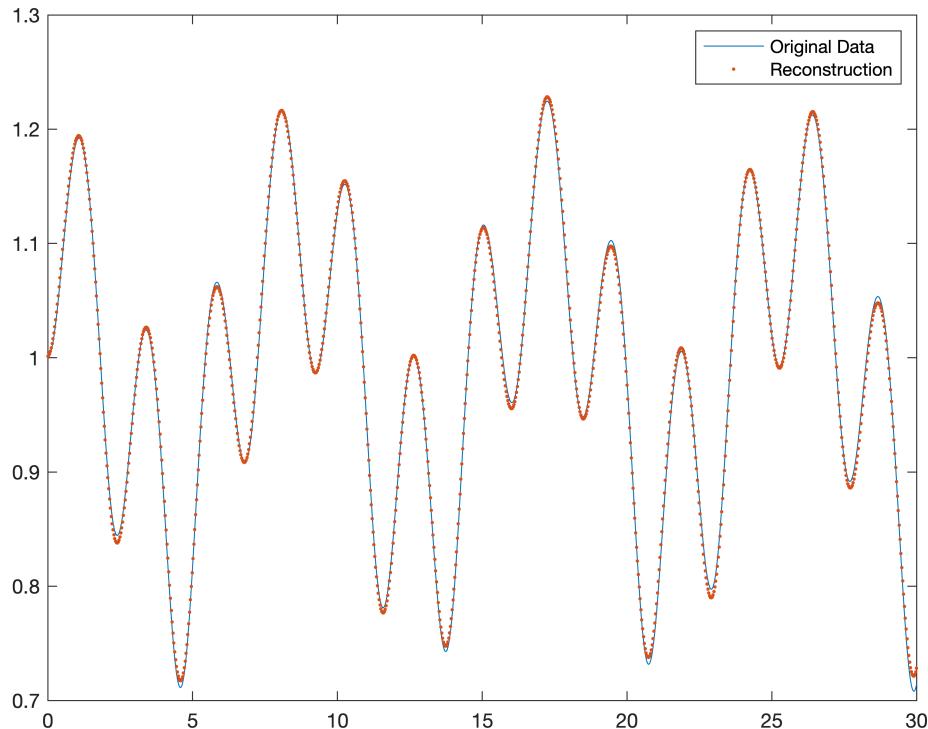
SVD is applied to \tilde{t}_k , a second dimension reduction that gives a new set of enlarged dimension-reduced snapshots, $\hat{\tilde{t}}_k$

which will satisfy - $\hat{\tilde{t}}_{k+1} = \hat{R}^t \cdot \hat{\tilde{t}}_k$, where \hat{R}^t is computed via the pseudo-inverse as defined above.

```
t = linspace(0,30,1000);
V = sqrt(1 + (1/2).*sin(t).*sin(sqrt(3)*t));
d = 800;
varepsilon1 = 10^-10;
varepsilon = 10^-4;
figure
[Vreconst,~] = DMDd_SIADS(d,V,t,varepsilon1,varepsilon)
```

```
Vreconst = 1x1000 complex
1.0012 + 0.0000i 1.0020 + 0.0000i 1.0034 + 0.0000i 1.0057 + 0.0000i ...
```

```
plot(t,V)
hold on
plot(t,real(Vreconst),'.')
legend("Original Data", "Reconstruction")
```



```
% Import data from text file
% Script for importing data from the following text file:
%
```

```

%     filename: /Volumes/Rohith/College/SpatioTemporalKoopman/data/BTC-USD_daily-06_02-24_04.csv
%
% Auto-generated by MATLAB on 03-Jun-2021 10:10:32

% Set up the Import Options and import the data
opts = delimitedTextImportOptions("NumVariables", 7);

% Specify range and delimiter
opts.DataLines = [2, Inf];
opts.Delimiter = ",";

% Specify column names and types
opts.VariableNames = ["Var1", "Var2", "Var3", "Var4", "Close", "Var6", "Var7"];
opts.SelectedVariableNames = "Close";
opts.VariableTypes = ["string", "string", "string", "string", "double", "string", "string"];

% Specify file level properties
opts.ExtraColumnsRule = "ignore";
opts.EmptyLineRule = "read";

% Specify variable properties
opts = setvaropts(opts, ["Var1", "Var2", "Var3", "Var4", "Var6", "Var7"], "WhitespaceRule", "pr");
opts = setvaropts(opts, ["Var1", "Var2", "Var3", "Var4", "Var6", "Var7"], "EmptyFieldRule", "au");

% Import the data
tbl = readtable("/Volumes/Rohith/College/SpatioTemporalKoopman/data/BTC-USD_daily-06_02-24_04.csv");

% Convert to output type
Close = tbl.Close;

% Clear temporary variables
clear opts tbl

t = linspace(0,100,length(Close));
d = 46;
varepsilon1 = 10^-10;
varepsilon = 10^-4;
[Vreconst,~] = DMDd_SIADS(d,Close',t,varepsilon1,varepsilon)

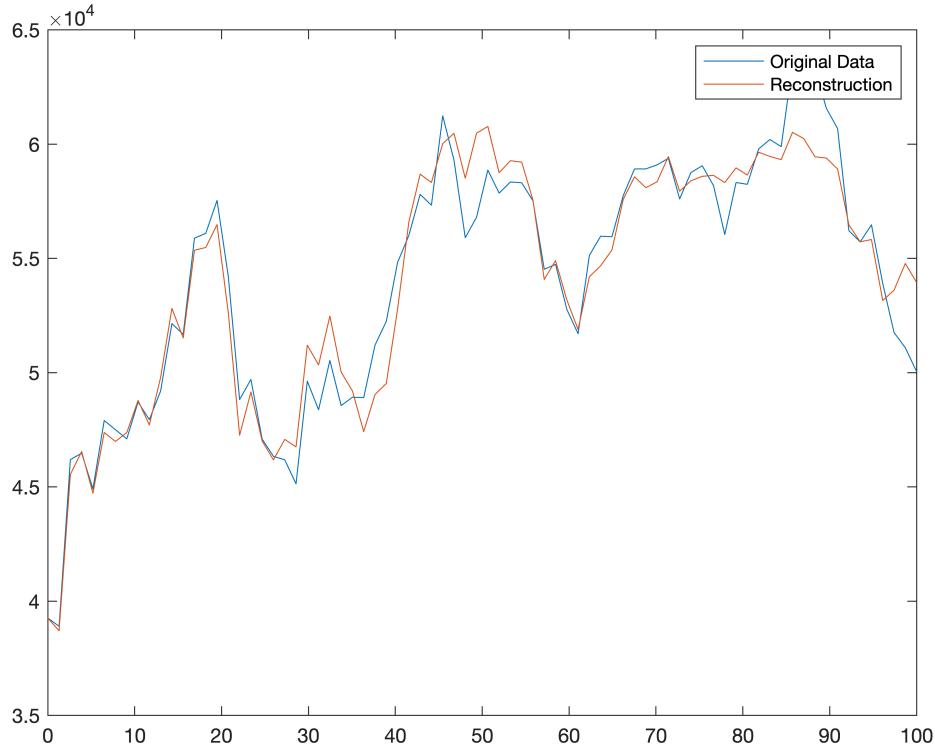
Vreconst = 1x78 complex
10^4 ×
3.9266 + 0.0000i 3.8704 - 0.0000i 4.5549 - 0.0000i 4.6551 - 0.0000i ...

```

```

figure
plot(t,Close)
hold on
plot(t,real(Vreconst))
legend("Original Data", "Reconstruction")

```



Spatio Temporal Koopman Decomposition

For simplicity purpose we will consider one spatio-variable X and a temporal-variable T for and snapshot V_1^k of dimension J x K.

Lets consider a toy model with discritised values $x_j = x_1 + j\Delta x$ and $t_j = t_1 + k\Delta t$, for $j = 1, \dots, J$ and $k = 1, \dots, K$

STKD can be represented by

$$v(x_j, t_k) = \sum_{m,n} a_{mn} u_{mn} e^{(v_m + ik_m)x_j + (\delta_n + i\omega_m)t_k}$$

u_n are conveniently normalized spatial modes, $a_n > 0$ are the mode amplitudes, and δ_n and ω_m are the associated

growth rates and frequencies, respectively.

STEP : 1 -

As in HODMD, SVD is performed on the Snapshot V_1^k with a tunable value ϵ_1 which determines the number of SVD modes M.

$$V_1^k = P \sum Q^T \equiv (\hat{X}_1^J)^T \hat{T}_1^k,$$

$$\hat{X}_1^J = \sqrt{\sum P^T}$$

$$\hat{T}_1^J = \sqrt{\sum Q^T}$$

These matrices are the reduced spatial and temporal snapshots and their columns are \hat{x}_j and \hat{t}_k are the reduced spatial and temporal snapshots.

STEP : 2 -

The HODMD algorithm is applied to the spatial and temporal components

$$\hat{x}_j \approx \sum_{m=1}^M \hat{a}_m^x \cdot \hat{q}_m^x e^{(v_m + ik_m)x_j}, \text{ for } j=1, \dots, J$$

$$\hat{t}_k \approx \sum_{n=1}^N \hat{a}_n^t \cdot \hat{q}_n^t e^{(\delta_n + i\omega_n)t_k}, \text{ for } k=1, \dots, K$$

The numbers of retained modes, M and N, are the *spatial and temporal complexities*, respectively, and are selected in terms of the spatial

and temporal amplitudes, \hat{a}_m^x and \hat{a}_n^t . M and N are the smallest values of the indexes and such that

$$\frac{\hat{a}_{M+1}^x}{\hat{a}_1^x} < \varepsilon_2$$

$$\frac{\hat{a}_{N+1}^t}{\hat{a}_1^t} < \varepsilon_2$$

Illustration of the STKD in a toy model,

$$u(x, t) = (0.5 + \sin(x)).[2.\cos(k_1 \cdot x - w_1 \cdot t) + (0.5).\cos(k_2 \cdot x - w_2 \cdot t)]$$

```

x = linspace(0,10,100);
t = linspace(0,100,100);
U = zeros(length(x));

varepsilon1 = 10^-8;
varepsilon2 = 10^-7;

for i=1:length(x)
    for j=1:length(t)
        X = x(i); T = t(j);
        U(i,j) = (0.5 + sin(X)) * (2*cos(2*X - (2*pi/45)*T) + 0.5*cos(10*X - sqrt(10)*T));
    end
end
figure
[Vreconst,Modes,Amplitudes,Amplitudesx,GrowthRateX,FrequencyX,AmplitudeST,GrowthRateT,FrequencyT,CalculateDMDdSdT(10,1,x,t,U,varepsilon1,varepsilon2)];

```

Spatial Dimension: singular values

```
Spatial dimension reduction
```

```
12
```

```
size of a
```

```
ans = 1x2
```

```
12 1
```

```
size of Q
```

```
ans = 1x2
```

```
4 12
```

```
Spectral complexity
```

```
12
```

```
ans =
```

```
'Spectral complexity'
```

```
kk3 = 4
```

```
48
```

```
12
```

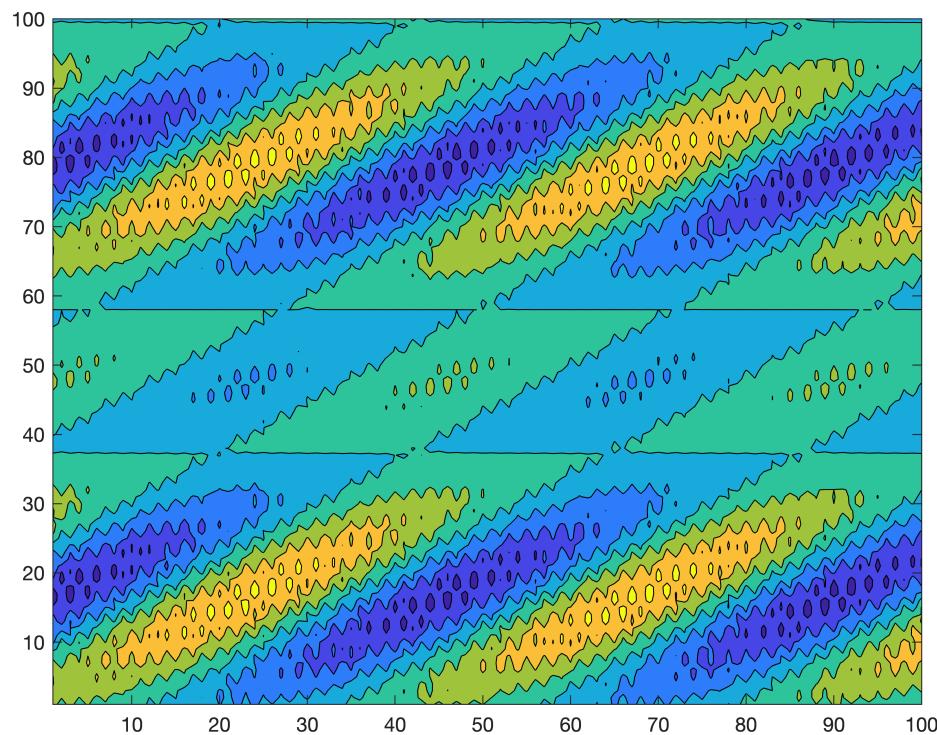
```
Number of spatial modes
```

```
12
```

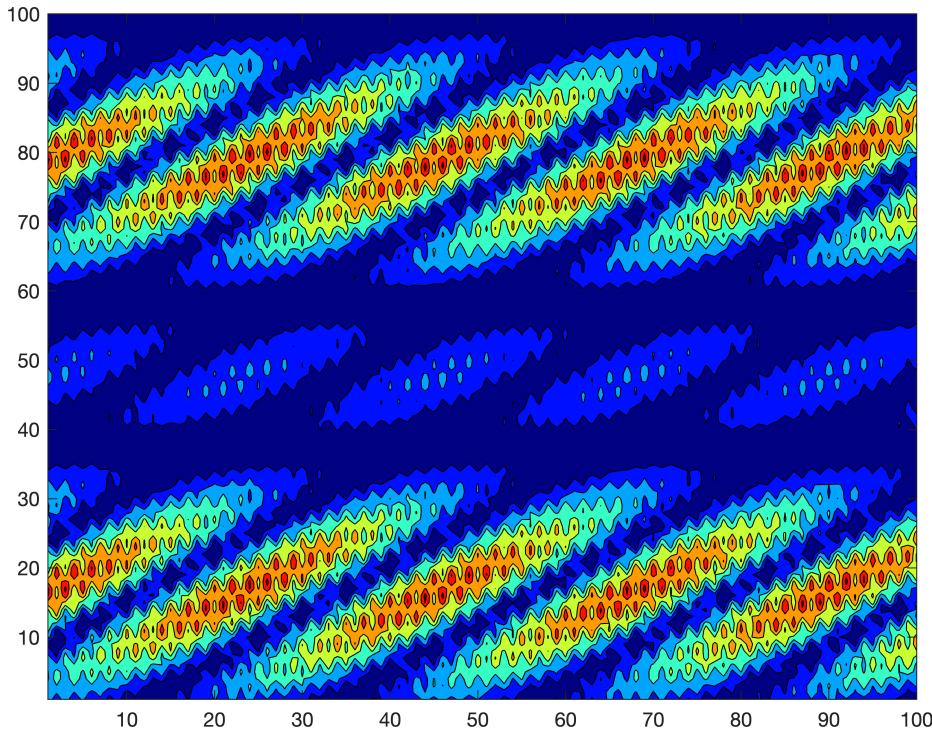
```
Number of temporal modes
```

```
4
```

```
contourf(U)
```



```
figure
contourf(abs(Vreconst))
shading('interp')
colormap(jet)
```



Stock Prediction via STKD

The information shared on social media generates sentiments and reactions in investors that influence their decisions to buy or sell financial assets, especially on the stock market [1]. News shared on social media, whether true or not, cause changes in the trends of international stock market indices [2]. Some studies confirm the relationship between sentiments generated by social media in investors and market trends, and the current study continues this path in exploring pandemic periods with a lexicon-based approach to detect polarity in financial news on Twitter.

Our hypothesis is that sentiments expressed via Tweets and News can cause a potential change in stock and could be a crucial factor for predicting very volatile prices such as **Cryptocurrency**. In the recent times, we saw how Elon Musk's tweets single-handedly brought down the price of Bitcoin and skyrocketed Dogecoin's price.

In the experiment performed, we will be collecting News and Tweets and analysing the sentiments of the same which will act as the spatial component of our analysis and temporal being time.

Bitcoin prediction with Tweets

For this experiment, tweets between 6th February to 24th April 2021 were collected along with the closing price of Bitcoin in the same Date range. The collected tweets will have numerous tweets for any given day hence a mean of all the sentiments for the day was taken.

The sentiment analysis was done in python using '*nlptown/bert-base-multilingual-uncased-sentiment*'

```
path = os.path.join(os.getcwd(), 'data', 'Bitcoin_tweets.csv')
```

```
data = pd.read_csv(path)

data.drop(columns=['user_name', 'user_location', 'user_description', 'user_created',
                   'user_followers', 'user_friends', 'user_favourites', 'user_verified',
                   'hashtags', 'source', 'is_retweet'], inplace=True)
text = data['text'].fillna("#").tolist()

tokenizer = AutoTokenizer.from_pretrained('nlptown/bert-base-multilingual-uncased-sentiment')

model = AutoModelForSequenceClassification.from_pretrained('nlptown/bert-base-multilingual-uncased-sentiment')

def sentiment_score(review):
    tokens = tokenizer.encode(review, return_tensors='pt')
    result = model(tokens)
    return int(torch.argmax(result.logits))+1

sent=[]
for i in tqdm(text):
    sent.append(sentiment_score(p.clean(i)))

data['sent'] = pd.DataFrame(sent)
```

The above code corresponds to the python script for extracting sentiments.

Since the data isn't very huge, a single snapshot will be very sparse.

```

clc
clear all

load sent.snp.mat
V = sent;
s = size(V);
Time = linspace(0,1,s(2));
Exis = linspace(0,1,s(1));

% APPLY STKD TO V
[J,K]=size(V);

%%%%%%%%%%%%% STKD PARAMETERS %%%%%%
%%%%%%%%%%%%% SET PARAMETERS STKD
% Tolerances
% SVD
varepsilon1=1e-8;
% DMD
varepsilon2=1e-7;
% Set index d: dSpace for spatial analysis and dTime for temporal analysis
dSpace=2;
dTime=1;

```

```
[Vreconst,Modes,Amplitudes,Amplitudesx,GrowthRatex,Frequencyx,Amplitudest,GrowthRatet,Frequency  
CalculateDMDdSdT(dSpace,dTime,Time,Exis,V,varepsilon1,varepsilon2);
```

```
Spatial Dimension: singular values  
18
```

```
Spatial dimension reduction  
20
```

```
Warning: Matrix is close to singular or badly scaled. Results may be inaccurate. RCOND = 2.692283e-17.
```

```
size of a
```

```
ans = 1×2
```

```
20 1
```

```
size of Q
```

```
ans = 1×2
```

```
18 20
```

```
Spectral complexity
```

```
20
```

```
ans =
```

```
'Spectral complexity'
```

```
kk3 = 18
```

```
360
```

```
360
```

```
Number of spatial modes
```

```
20
```

```
Number of temporal modes
```

```
18
```

% CALCULATE RRMS ERROR

```
dif=Vreconst-V;  
errorRMS=norm(dif(:))/norm(V(:));  
disp('Reconstruction error: RRMSE')
```

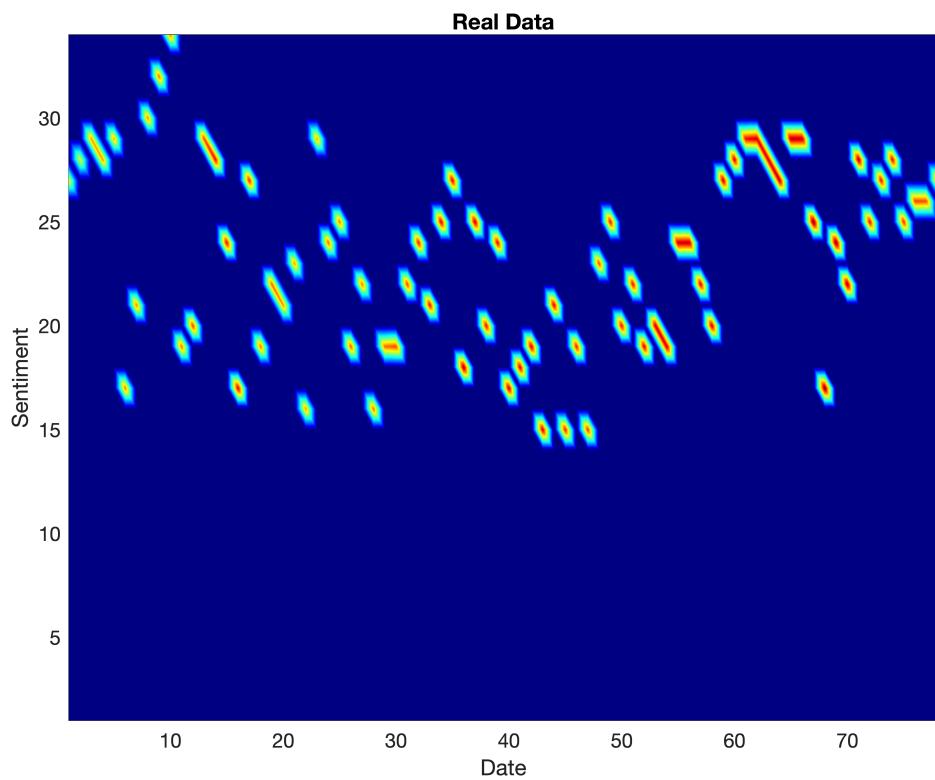
```
Reconstruction error: RRMSE
```

```
disp(errorRMS)
```

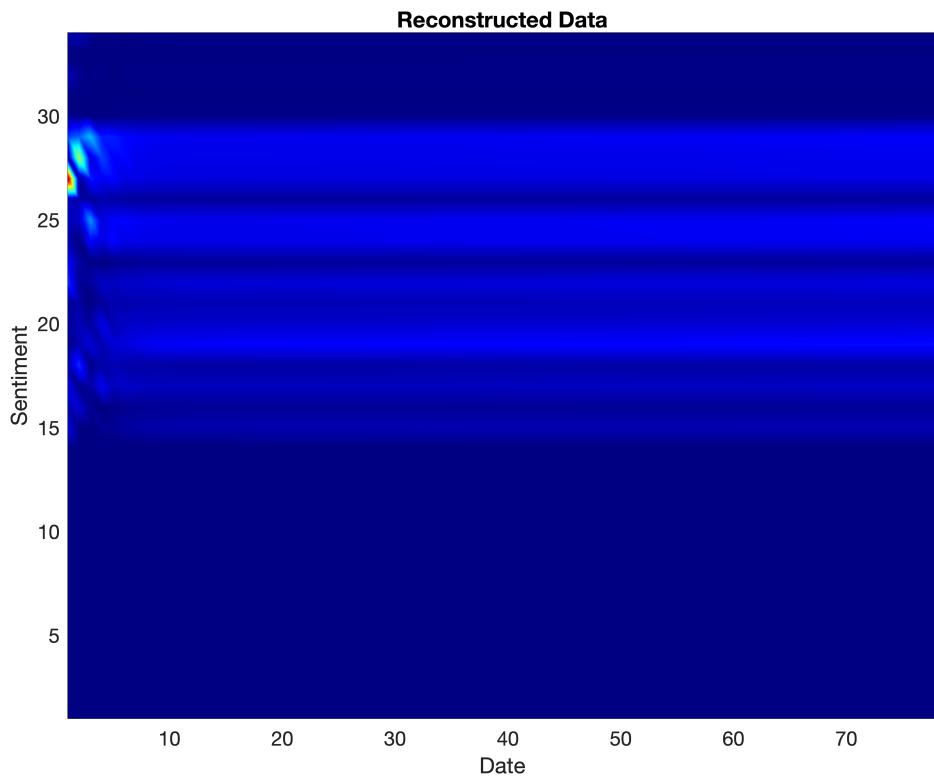
```
0.9540
```

% PLOT RECONSTRUCTION

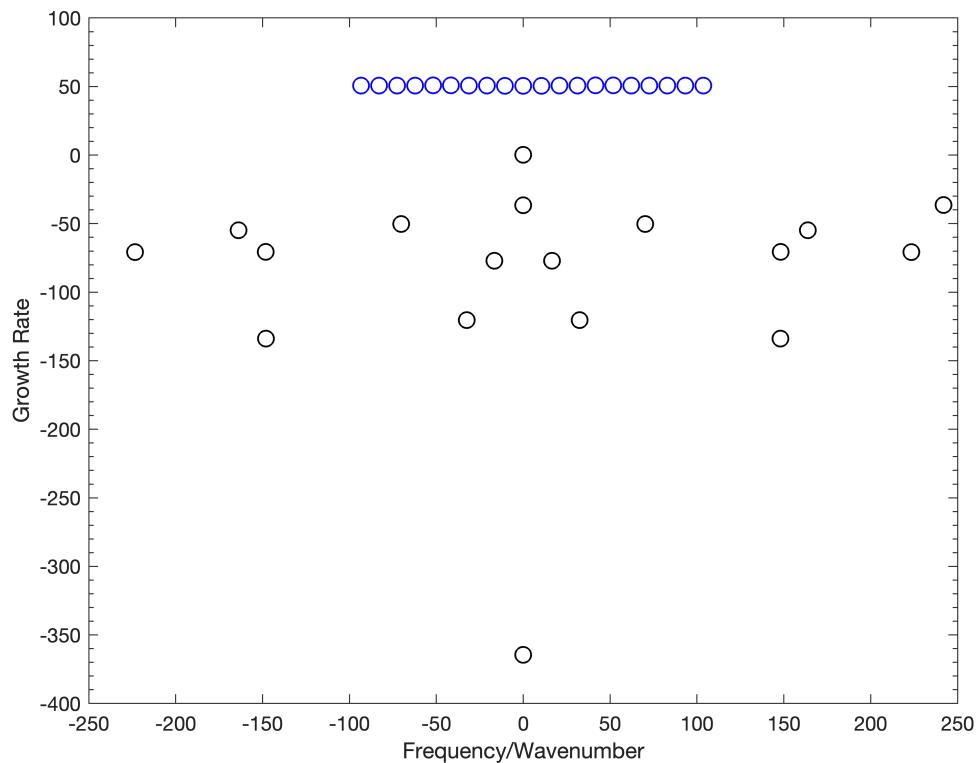
```
figure  
pcolor(V)  
shading('interp')  
colormap(jet)  
xlabel('Date')  
ylabel('Sentiment')  
title("Real Data")
```



```
h9=figure;
axes9 = axes('Parent',h9,'FontSize',14,'FontName','Agency FB');
box(axes9,'on');
pcolor(abs(Vreconst))
shading('interp')
colormap(jet)
xlabel('Date')
ylabel('Sentiment')
title("Reconstructed Data")
```



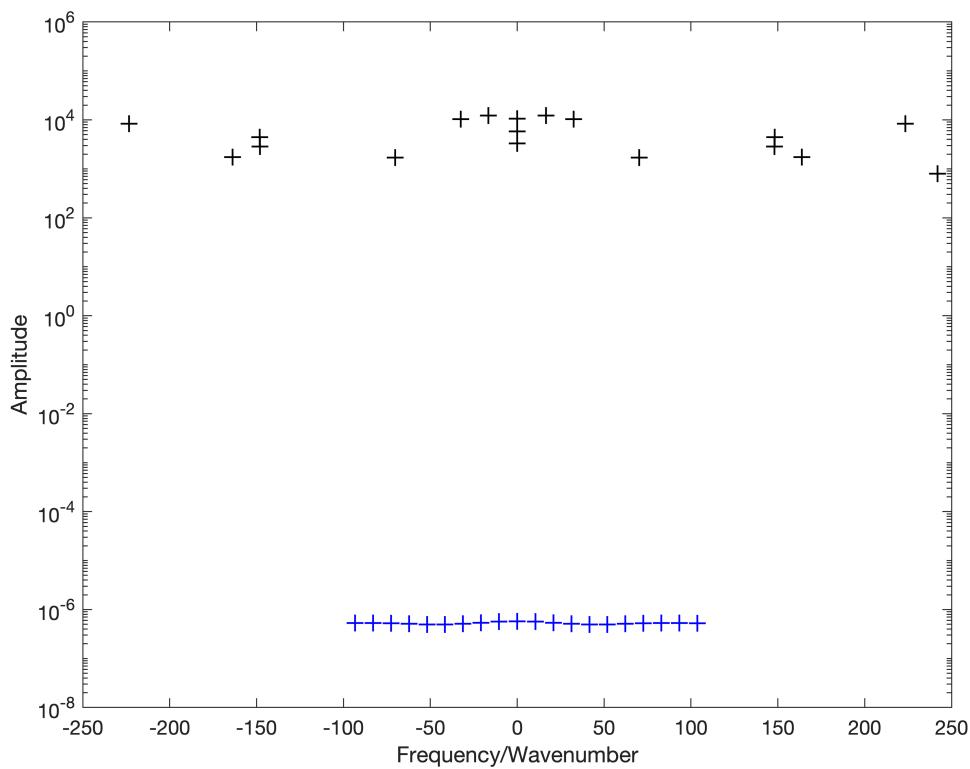
```
% Plot: frequency/wavenumber vs. amplitude, vs. growth rate
figure1 = figure;
axes1 = axes('Parent',figure1);
hold(axes1,'on');
box(axes1,'on');
semilogy(Frequencyt,GrowthRatet,'o','LineWidth',2,'color','k','MarkerSize',8);
semilogy(Frequencyx,GrowthRatex,'o','LineWidth',2,'color','b','MarkerSize',8);
set(axes1,'YMinorTick','on');
xlabel('Frequency/Wavenumber')
ylabel('Growth Rate')
```



```

figure1 = figure;
axes1 = axes('Parent',figure1);
hold(axes1,'on');
box(axes1,'on');
semilogy(Frequencyt,Amplitudest,'+', 'linewidth',2, 'color','k', 'MarkerSize',8);
semilogy(Frequencyx,Amplitudesx,'+', 'linewidth',2, 'color','b', 'MarkerSize',8);
set(axes1,'YMinorTick','on','YScale','log');
xlabel('Frequency/Wavenumber')
ylabel('Amplitude')

```



figure

Dogecoin prediction with News Sentiments

Similar to the Bitcoin approach, news was collected for the past 2 years - 1st January 2019 to 3rd June 2021.

```

frames=[]
delta = timedelta(days=1)
start_date = date(2019, 1, 1)
end_date = date(2021, 6, 3)
for i in tqdm(range(880)):
    s = start_date.strftime("%Y-%m-%d")
    e = (start_date+delta).strftime("%Y-%m-%d")
    response = datanews.news(q='Doge',from_date=s,to_date=e)
    articles = response['hits']
    d = pd.DataFrame(articles)
    frames.append(d)
    start_date+=delta
    if start_date>end_date:
        break
    time.sleep(1.5)

```

The full notebook can be found here : https://colab.research.google.com/drive/1YeivODqLAZtZiSBbuot7vV_T8ZkFzwEF?usp=sharing

```

clear all
clc
%Import data from text file
% Script for importing data from the following text file:

```



```

varepsilon=1e-18;
% Set index d: dSpace for spatial analysis and dTime for temporal analysis
dSpace=25;
dT=25;

[Vreconst,Modes,Amplitudes,Amplitudesx,GrowthRatex,Frequencyx,Amplitudest,GrowthRatet,Frequencyt]
CalculateDMDdSdT(dSpace,dT,Time,Exis,V,varepsilon1,varepsilon2);

```

Spatial Dimension: singular values
50

Spatial dimension reduction
26

size of a
ans = 1x2
26 1
size of Q
ans = 1x2
50 26
Spectral complexity
26

Spatial dimension reduction
280

size of a
ans = 1x2
280 1
size of Q
ans = 1x2
50 280
Spectral complexity
280

Warning: Matrix is close to singular or badly scaled. Results may be inaccurate. RCOND = 4.209482e-17.

7280

7280

Number of spatial modes
26

Number of temporal modes
280

```

% CALCULATE RRMS ERROR
dif=Vreconst-V;
errorRMS=norm(dif(:))/norm(V(:));
disp('Reconstruction error: RRMSE')

```

Reconstruction error: RRMSE

```
disp(errorRMS)
```

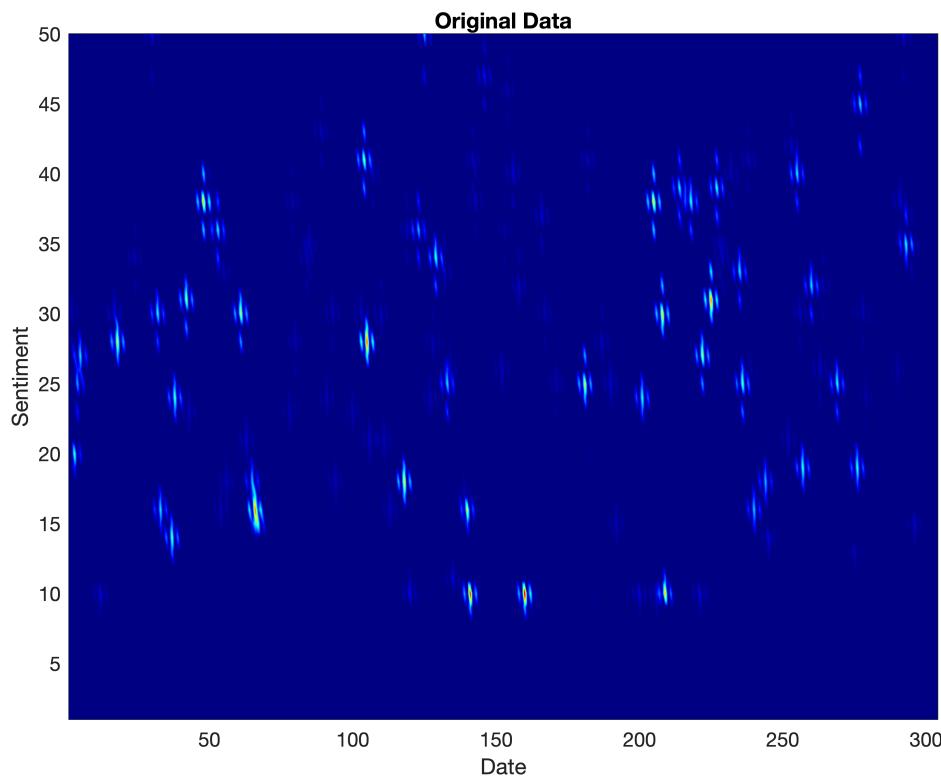
0.9998

```

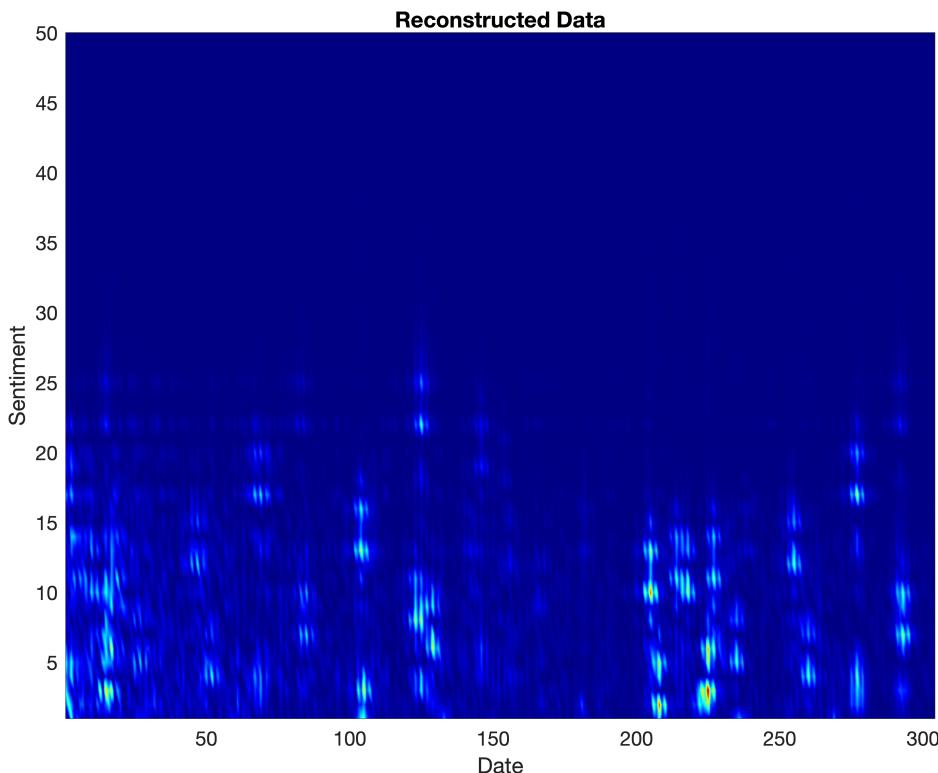
% PLOT RECONSTRUCTION
figure
pcolor(V)
shading('interp')

```

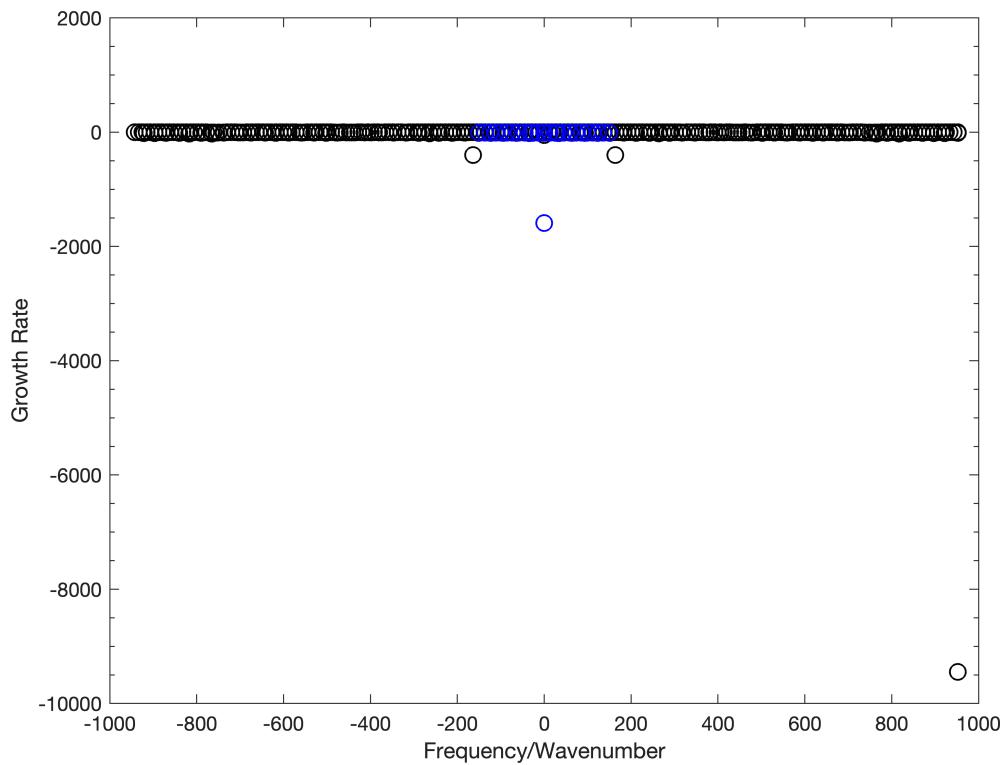
```
colormap(jet)
xlabel('Date')
ylabel('Sentiment')
title("Original Data")
```



```
h9=figure;
axes9 = axes('Parent',h9,'FontSize',14,'FontName','Agency FB');
box(axes9,'on');
pcolor(abs(Vreconst))
shading('interp')
colormap(jet)
xlabel('Date')
ylabel('Sentiment')
title("Reconstructed Data")
```



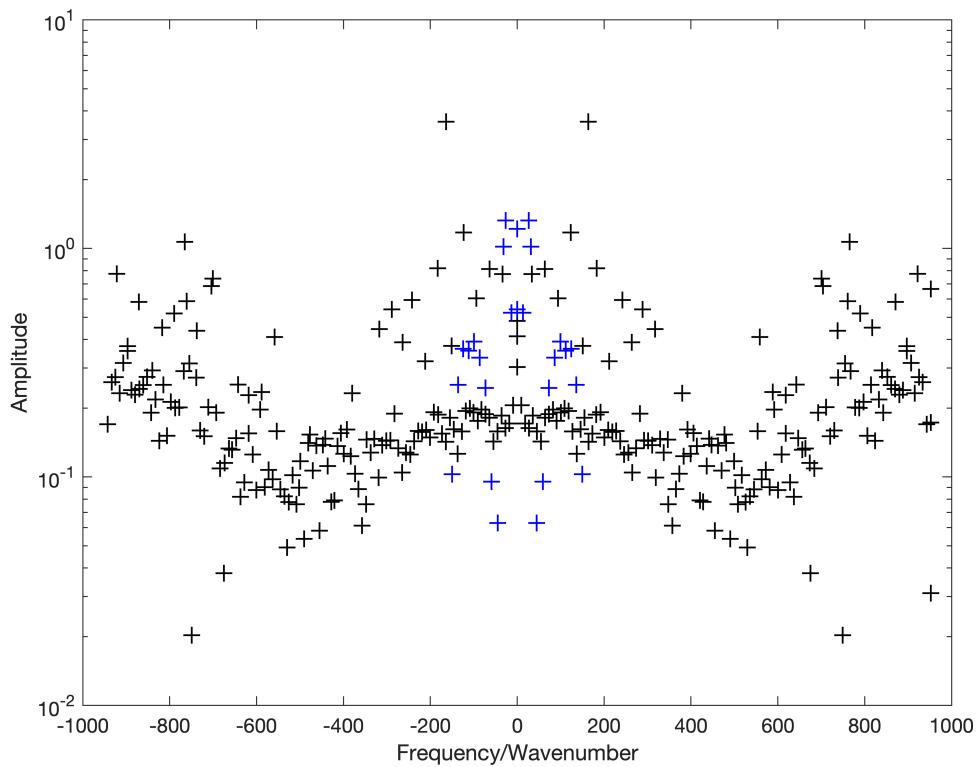
```
% Plot: frequency/wavenumber vs. amplitude, vs. growth rate
figure1 = figure;
axes1 = axes('Parent',figure1);
hold(axes1,'on');
box(axes1,'on');
semilogy(Frequencyt,GrowthRatet,'o','LineWidth',2,'Color','k','MarkerSize',8);
semilogy(Frequencyx,GrowthRatex,'o','LineWidth',2,'Color','b','MarkerSize',8);
set(axes1,'YMinorTick','on');
xlabel('Frequency/Wavenumber')
ylabel('Growth Rate')
```



```

figure1 = figure;
axes1 = axes('Parent',figure1);
hold(axes1,'on');
box(axes1,'on');
semilogy(Frequencyt,Amplitudest,'+', 'linewidth',2, 'color','k', 'MarkerSize',8);
semilogy(Frequencyx,Amplitudesx,'+', 'linewidth',2, 'color','b', 'MarkerSize',8);
set(axes1,'YMinorTick','on','YScale','log');
xlabel('Frequency/Wavenumber')
ylabel('Amplitude')

```



Conclusion

From the above experiments we can see that the snapshots (Data Matrix) is very sparse and STKD is not very sucessful in reconstrcting the snapshot. A few reasons could be/scope of improvement:

- Incorrect Choice of Space Variable
- Use of improved Sentiment Analyser
- Hypertuning parameters of STKD
- Restriction in Data Collection
- More weightage to Tweets from celebrities (eg:Elon Musk's tweet would be more important than any unknown individual)

Despite the result, this experiment was conducted to analyse if sentiments from twitter and News could potentially aid in predicting Volatile Markets. These experiments would be a base for further improvement and analysis.

Reference

- [1] Kearney C, Liu S. Textual sentiment in finance: a survey of methods and models. *Int Rev Financ Anal.* 2014;33:171–85.
- [2] Jiao P, Veiga A, Walther A. Social media, news media and the stock market. *J Econ Behav Organ.* 2020;176:63–90.

Appendix

```
function [Vreconst,deltas,omegas,amplitude,modes] =DMDd_SIADS(d,V,Time,varepsilon1,varepsilon0)

%%%%%%%%%%%%%%%
%%% This function solves the HODMD algorithm presented in %%%
%%% Le Clainche & Vega, SIAM J. on Appl. Dyn. Sys. 16(2):882-925, 2017 %%%
%%%%%%%%%%%%%%%
%%% % INPUT: %
%%% d: parameter of DMD-d (higher order Koopman assumption)
%%% V: snapshot matrix
%%% Time: vector time
%%% varepsilon1: first tolerance (SVD)
%%% varepsilon0: second tolerance (DMD-d modes)
%%% % OUTPUT: %
%%% Vreconst: reconstruction of the snapshot matrix V
%%% deltas: growth rate of DMD modes
%%% omegas: frequency of DMD modes(angular frequency)
%%% amplitude: amplitude of DMD modes
%%% modes: DMD modes
%%%%%%%%%%%%%%%

[J,K]=size(V);

% STEP 1: SVD of the original data

[U,Sigma,T]=svd(V, 'econ');
sigmas=diag(Sigma);
n=length(sigmas);

NormS=norm(sigmas,2);
kk=0;
for k=1:n
    if norm(sigmas(k:n),2)/NormS>varepsilon1
        kk=kk+1;
    end
end

U=U(:,1:kk);

% Create reduced snapshots matrix
hatT=Sigma(1:kk,1:kk)*T(:,1:kk)';
[N,~]=size(hatT);

% Create the modified snapshot matrix
tildeT=zeros(d*N,K-d+1);
for ppp=1:d
    tildeT((ppp-1)*N+1:ppp*N,:)=hatT(:,ppp:ppp+K-d);
end
```

```

% Dimension reduction
[U1,Sigma1,T1]=svd(tildeT,'econ');
sigmas1=diag(Sigma1);

Deltat=Time(2)-Time(1);
n=length(sigmas1);

NormS=norm(sigmas1,2);
kk1=0;
for k=1:n
    RRMSEE(k)=norm(sigmas1(k:n),2)/NormS;
    if RRMSEE(k)>varepsilon1
        kk1=kk1+1;
    end
end

U1=U1(:,1:kk1);
hatT1=Sigma1(1:kk1,1:kk1)*T1(:,1:kk1)';

% Reduced modified snapshot matrix
[~,K1]=size(hatT1);
[tildeU1,tildeSigma,tildeU2]=svd(hatT1(:,1:K1-1),'econ');

% Reduced modified Koopman matrix
tildeR=hatT1(:,2:K1)*tildeU2*inv(tildeSigma)*tildeU1';
[tildeQ,tildeMM]=eig(tildeR);
eigenvalues=diag(tildeMM);

M=length(eigenvalues);
qq=log(eigenvalues);
deltas=real(qq)/Deltat;
omegas=imag(qq)/Deltat;

Q=U1*tildeQ;
Q=Q((d-1)*N+1:d*N,:);
[NN,MMM]=size(Q);

for m=1:MMM
    NormQ=Q(:,m);
    Q(:,m)= Q(:,m)/norm(NormQ(:,2));
end

% Calculate amplitudes
Mm=zeros(NN*K,M);
Bb=zeros(NN*K,1);
aa=eye(MMM);
for k=1:K
    Mm(1+(k-1)*NN:k*NN,:)=Q*aa;
    aa=aa*tildeMM;
    Bb(1+(k-1)*NN:k*NN,1)=hatT(:,k);
end

```

```

[Ur,Sigmar,Vr]=svd(Mm, 'econ');
a=Vr*(Sigmar\ (Ur'*Bb));

u=zeros(NN,M);
for m=1:M
    u(:,m)=a(m)*Q(:,m);
end
amplitude=zeros(M,1);

for m=1:M
    aca=U*u(:,m);
    amplitude(m)=norm(aca(:,2))/sqrt(J);
end

UU=[u; deltas'; omegas'; amplitude']';
UU1=sortrows(UU, -(NN+3));

UU=UU1';
u=UU(1:NN,:);
deltas=UU(NN+1,:);
omegas=UU(NN+2,:);
amplitude=UU(NN+3,:);
kk3=0;

for m=1:M
    if amplitude(m)/amplitude(1)>varepsilon
        kk3=kk3+1;
    else
    end
end

u=u(:,1:kk3);
deltas=deltas(1:kk3);
omegas=omegas(1:kk3);
amplitude=amplitude(1:kk3);

% Reconstruction of the original snapshot matrix
hatTreconst=zeros(N,K);
for k=1:K
    hatTreconst(:,k)= ContReconst_SIADS(Time(k),Time(1),u,deltas,omegas);
end

Vreconst=U*hatTreconst;

% Calculation of DMD modes
modes=zeros(J,kk3);
amplitude0=zeros(kk3,1);
for m=1:kk3
    NormMode=norm(U*u(:,m),2)/sqrt(J);
    amplitude0(m)=NormMode;
    modes(:,m)=U*u(:,m)/NormMode;
end
end

```

