SPECTRAL VISIBILITY GRAPHS

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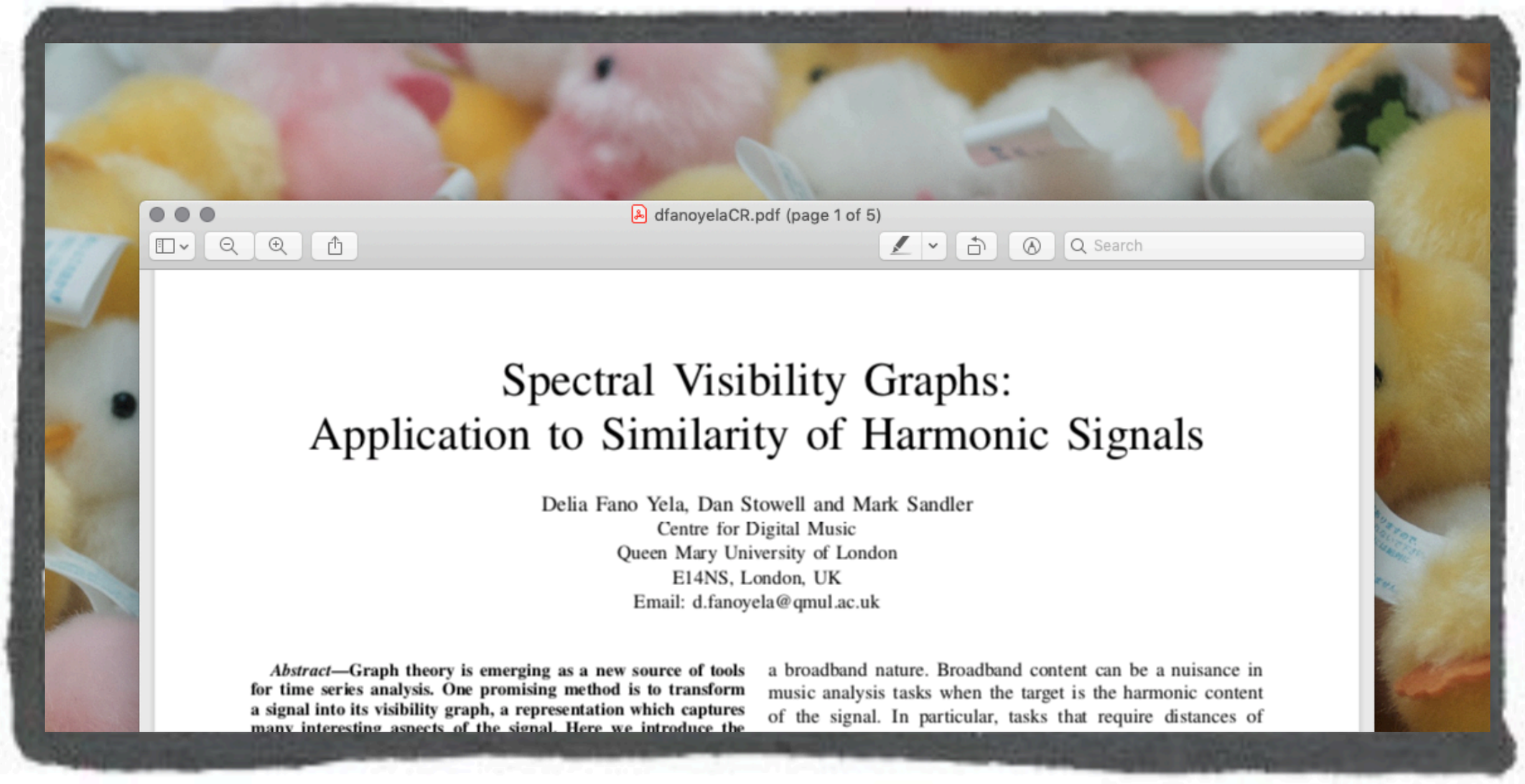

SPECTRAL VISIBILITY GRAPHS

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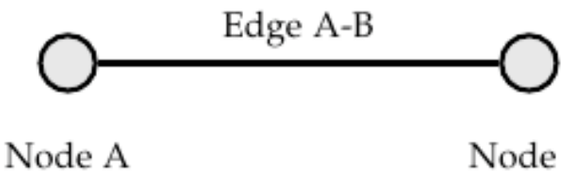
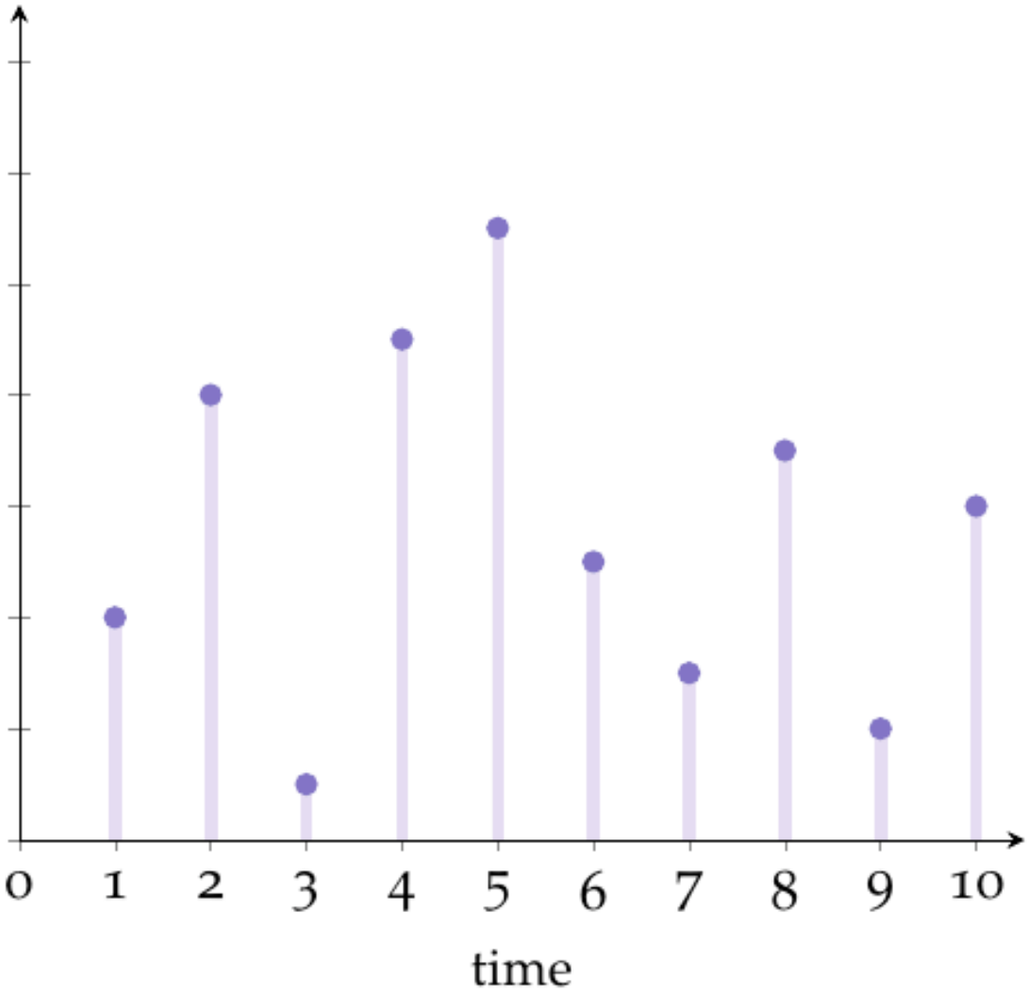
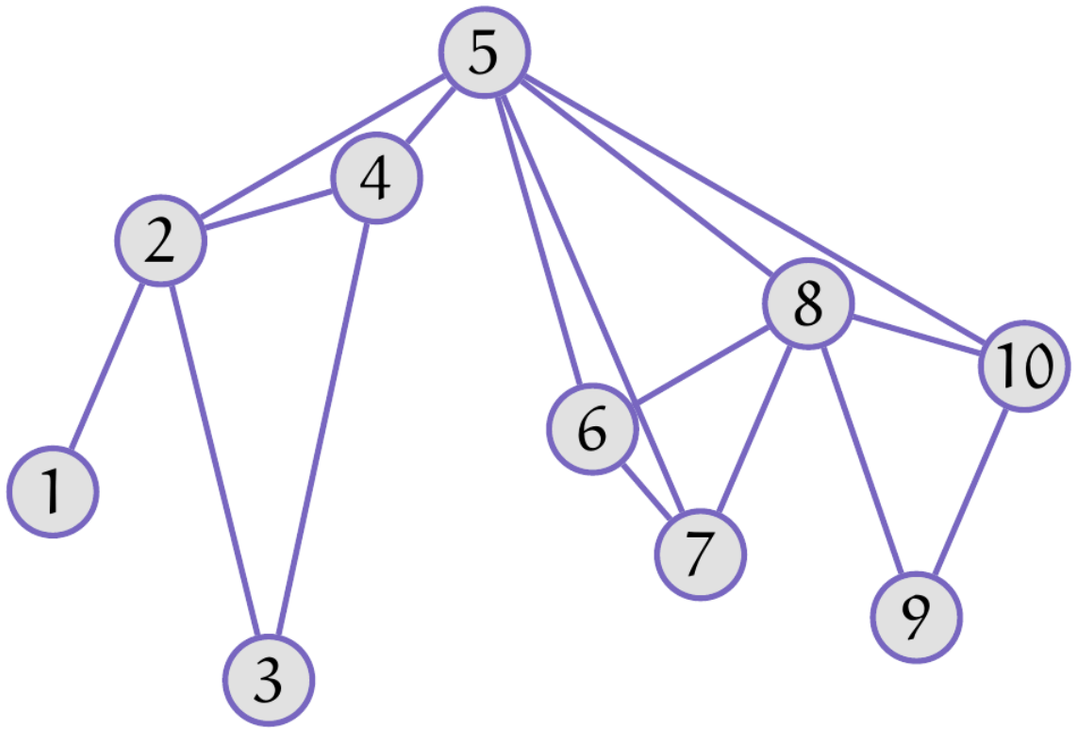


SPECTRAL VISIBILITY GRAPHS

VISIBILITY GRAPHS





From time series to complex networks: The visibility graph

Lucas Lacasa*†, Bartolo Luque*, Fernando Ballesteros‡, Jordi Luque§, and Juan Carlos Nuño¶

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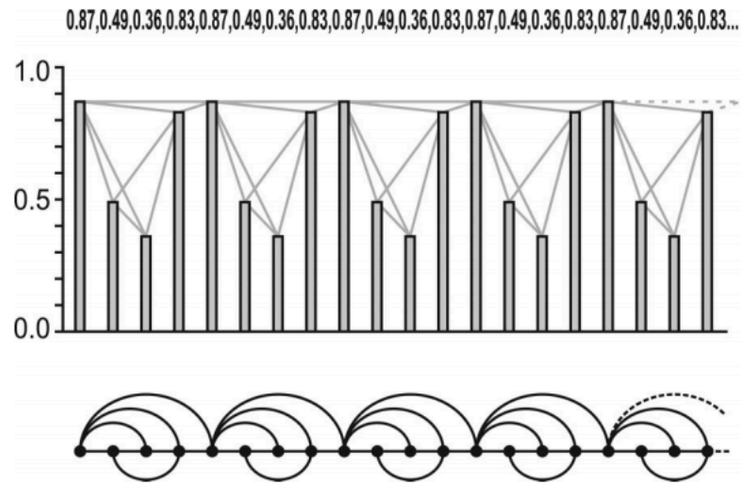
In this work we present a simple and fast computational method, the *visibility algorithm*, that converts a time series into a graph. The constructed graph inherits several properties of the series in its structure. Thereby, periodic series convert into regular graphs, and random series do so into random graphs. Moreover, fractal series convert into scale-free networks, enhancing the fact that power law degree distributions are related to fractality, something highly discussed recently. Some remarkable examples and analytical tools are outlined to test the method's reliability. Many different measures, recently developed in the complex network theory, could by means of this new approach characterize time series from a new point of view.

Brownian motion | complex systems | fractals



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PHYSICAL REVIEW E **82**, 036120 (2010)

Description of stochastic and chaotic series using visibility graphs

Lucas Lacasa and Raul Toral*

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(Received 28 July 2010; published 29 September 2010)

Nonlinear time series analysis is an active field of research that studies the structure of complex signals in order to derive information of the process that generated those series, for understanding, modeling and forecasting purposes. In the last years, some methods mapping time series to network representations have been proposed. The purpose is to investigate on the properties of the series through graph theoretical tools recently developed in the core of the celebrated complex network theory. Among some other methods, the so-called visibility algorithm has received much attention, since it has been shown that series correlations are captured by the algorithm and translated in the associated graph, opening the possibility of building fruitful connections

From time series to complex networks: The visibility graph

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OPEN

Multiplex visibility graphs to investigate recurrent neural network dynamics

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Filippo Maria Bianchi[1], Lorenzo Livi[2], Cesare Alippi[3,4] & Robert Jenssen[1]

A recurrent neural network (RNN) is a universal approximator of dynamical systems, whose performance often depends on sensitive hyperparameters. Tuning them properly may be difficult and, typically, based on a trial-and-error approach. In this work, we adopt a graph-based framework to interpret and characterize internal dynamics of a class of RNNs called echo state networks (ESNs). We design principled unsupervised methods to derive hyperparameters configurations yielding maximal ESN performance, expressed in terms of prediction error and memory capacity. In particular, we propose to model time series generated by each neuron activations with a horizontal visibility graph, whose topological properties have been shown to be related to the underlying system dynamics. Successively, horizontal visibility graphs associated with all neurons become layers of a larger structure called a multiplex. We show that topological properties of such a multiplex reflect important features of

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Description of stochastic and chaotic series using visibility graphs

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OPEN

Multiplex visibility graphs to investigate recurrent neural network dynamics

Received:
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Visibility graphs for image processing

Jacopo Iacovacci[1,2] and Lucas Lacasa[3]*

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[2] *The Molecular Biology of Metabolism Laboratory, The Francis Crick Institute, London NW11AT (United Kingdom) and*

[3] *School of Mathematical Sciences, Queen Mary University of London, E14NS London (United Kingdom)*

The family of image visibility graphs (IVG/IHVGs) have been recently introduced as simple algorithms by which scalar fields can be mapped into graphs. Here we explore the usefulness of such an operator in the scenario of image processing and image classification. We demonstrate that the link architecture of the image visibility graphs encapsulates relevant information on the

From time series to complex networks: The visibility graph

Lucas Lacasa*†, Bartolo Luque*, Fernando Ballesteros‡, Jordi Luque§, and Juan Carlos Nuño¶

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Visibility graphs for image processing

Jacopo Iacovacci[1,2] and Lucas Lacasa[3]*

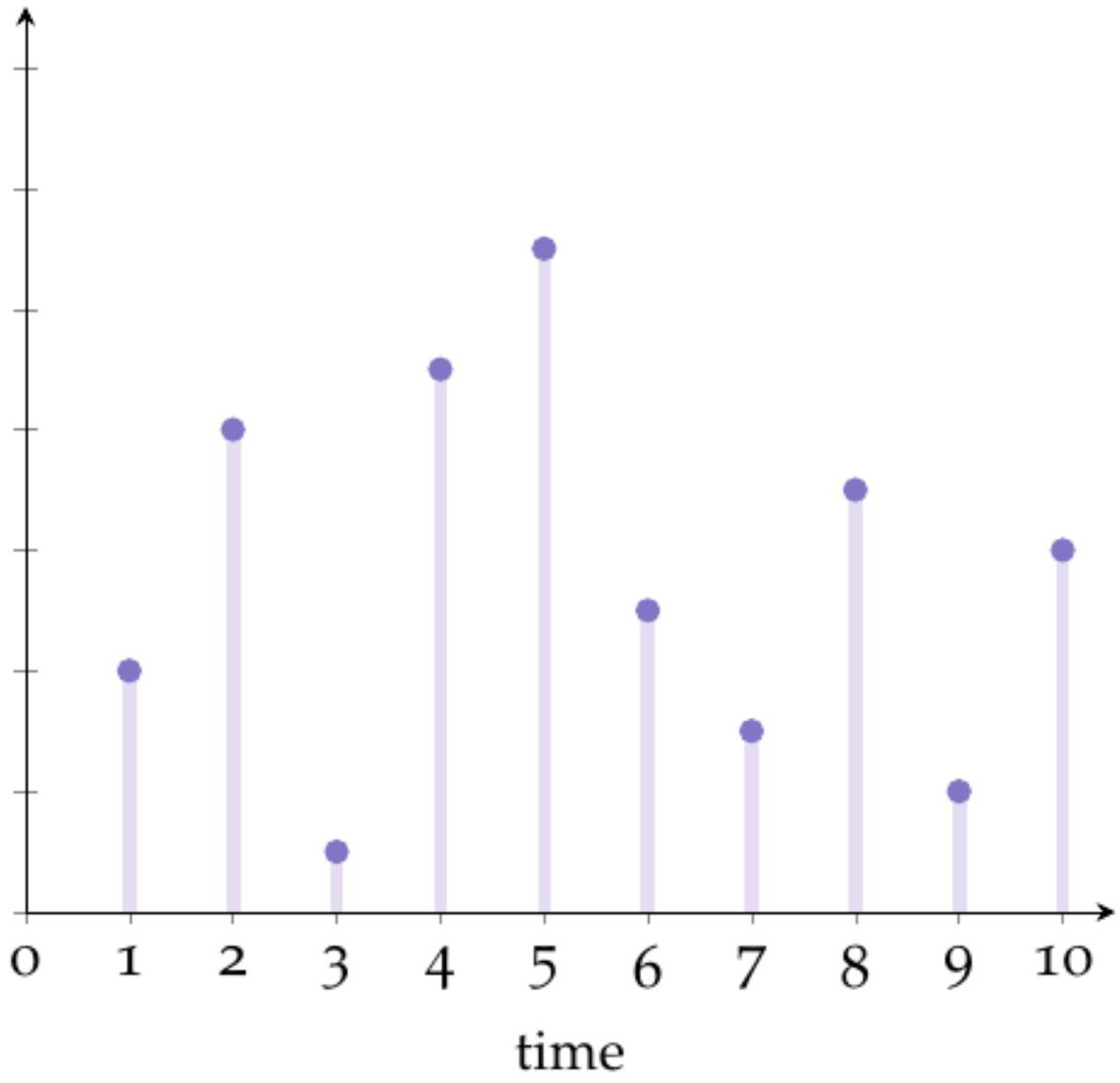
[1] *Department of Surgery and Cancer, Division of Computational and Systems Medicine,*

Horizontal Visibility Graphs as analysis tool for river runoff dynamics

Sebastian Sippel (1), Holger Lange (1), Osvaldo A. Rosso (2,3,4)

(1) Norwegian Institute of Bioeconomy Research, Terrestrial Ecology, Ås, Norway (holger.lange@nibio.no), (2) Instituto Tecnologico de Buenos Aires (ITBA), Ciudad Autonoma de Buenos Aires, Argentina, (3) Instituto de Fisica, Universidade Federal de Alagoas (UFAL), Maceio, Brazil, (4) Complex Systems Group, Facultad de Ingeniera y Ciencias Aplicadas, Universidad de los Andes, Santiago, Chile

Horizontal Visibility Graphs (HVGs) are a recently developed method to construct networks based on time series. Values (the nodes of the network) of the time series are linked to each other if there is no value higher between them. The network properties reflect the nonlinear dynamics of the time series.
For some classes of stochastic processes and for periodic time series, analytic results can be obtained for the degree distribution, the local clustering coefficient distribution, the mean path length, and others. HVGs have the potential to discern between deterministic-chaotic and correlated-stochastic time series.
We investigate a set of around 150 river runoff time series at daily resolution from Brazil with an average length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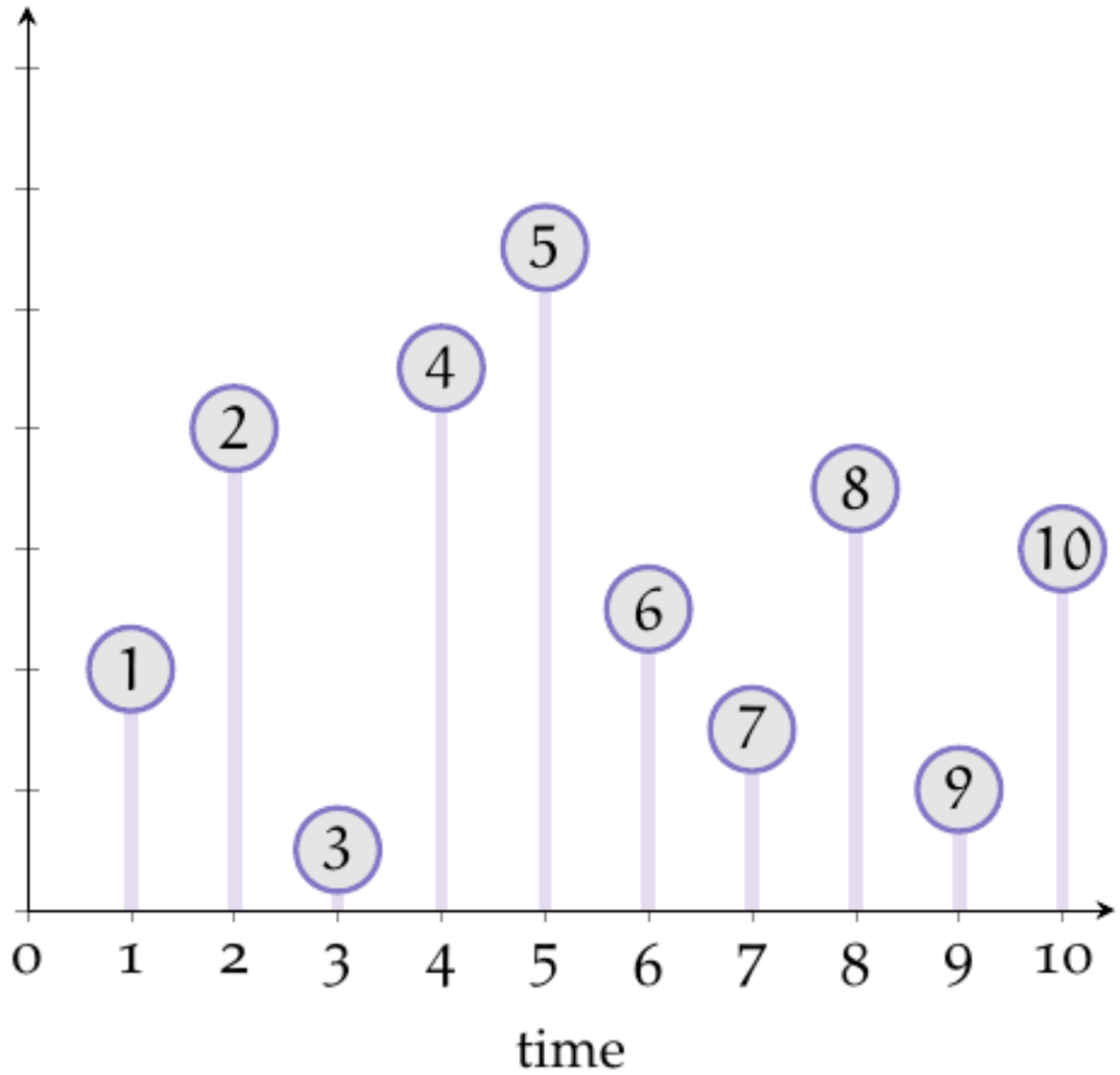
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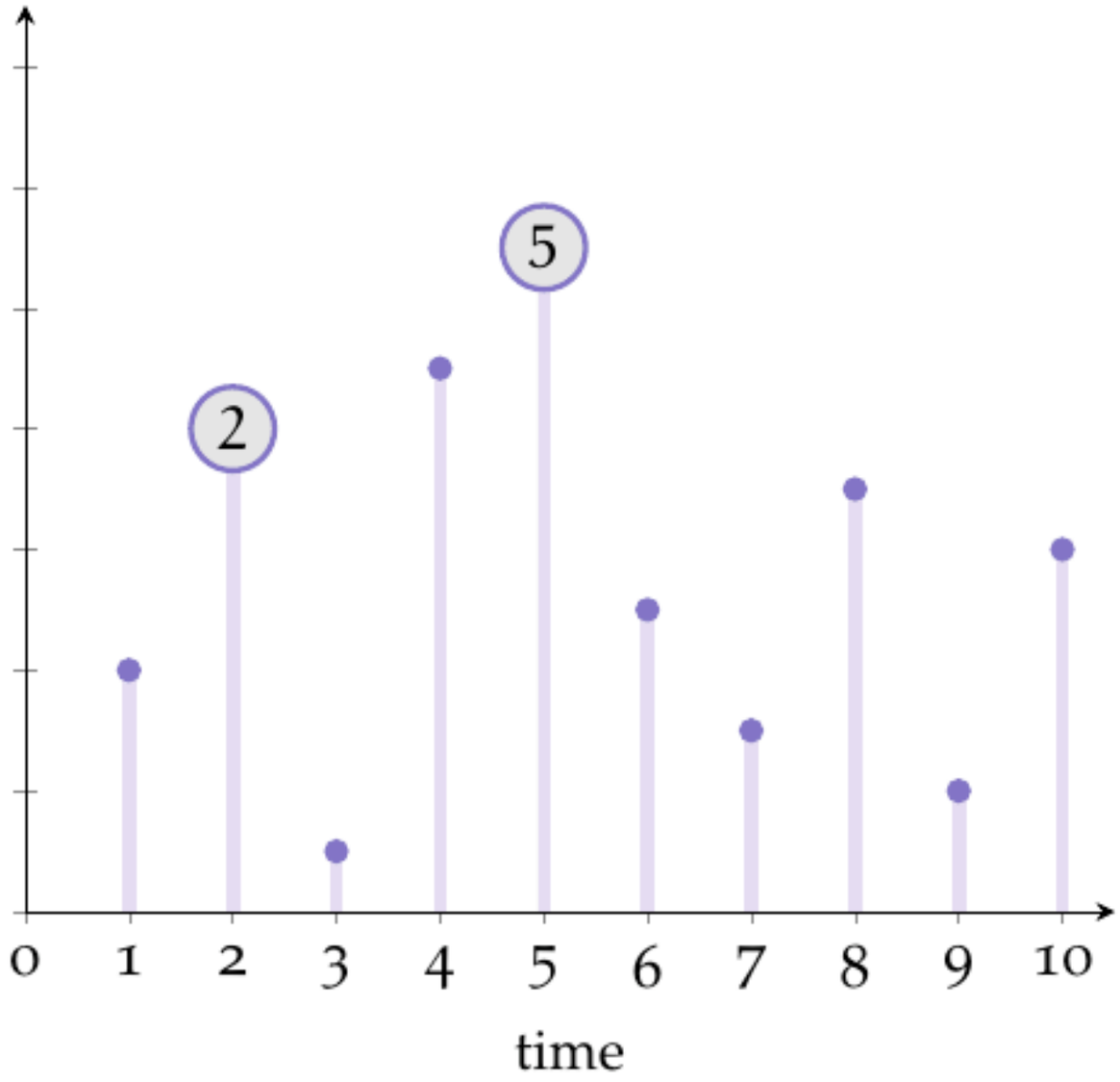
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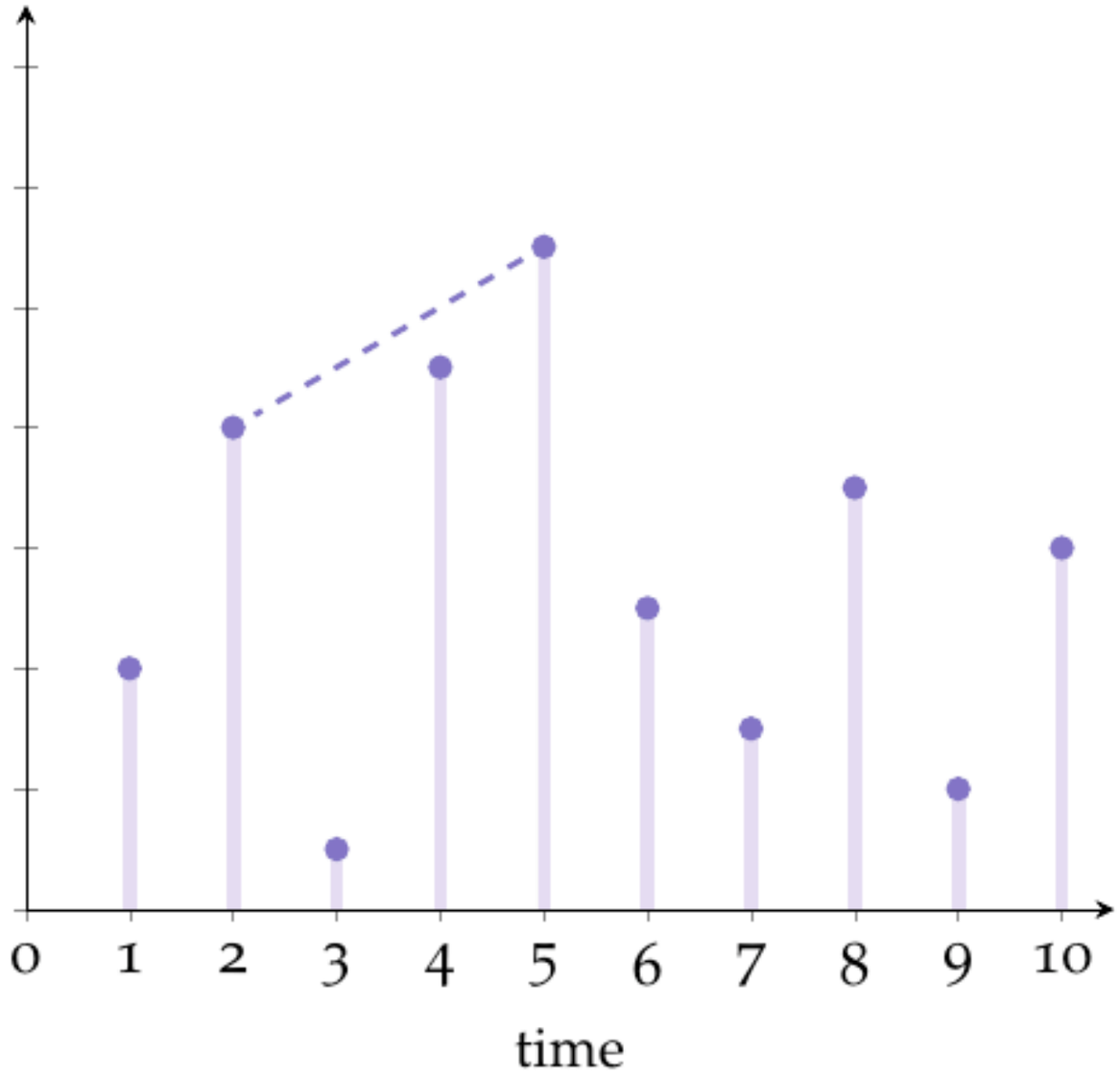
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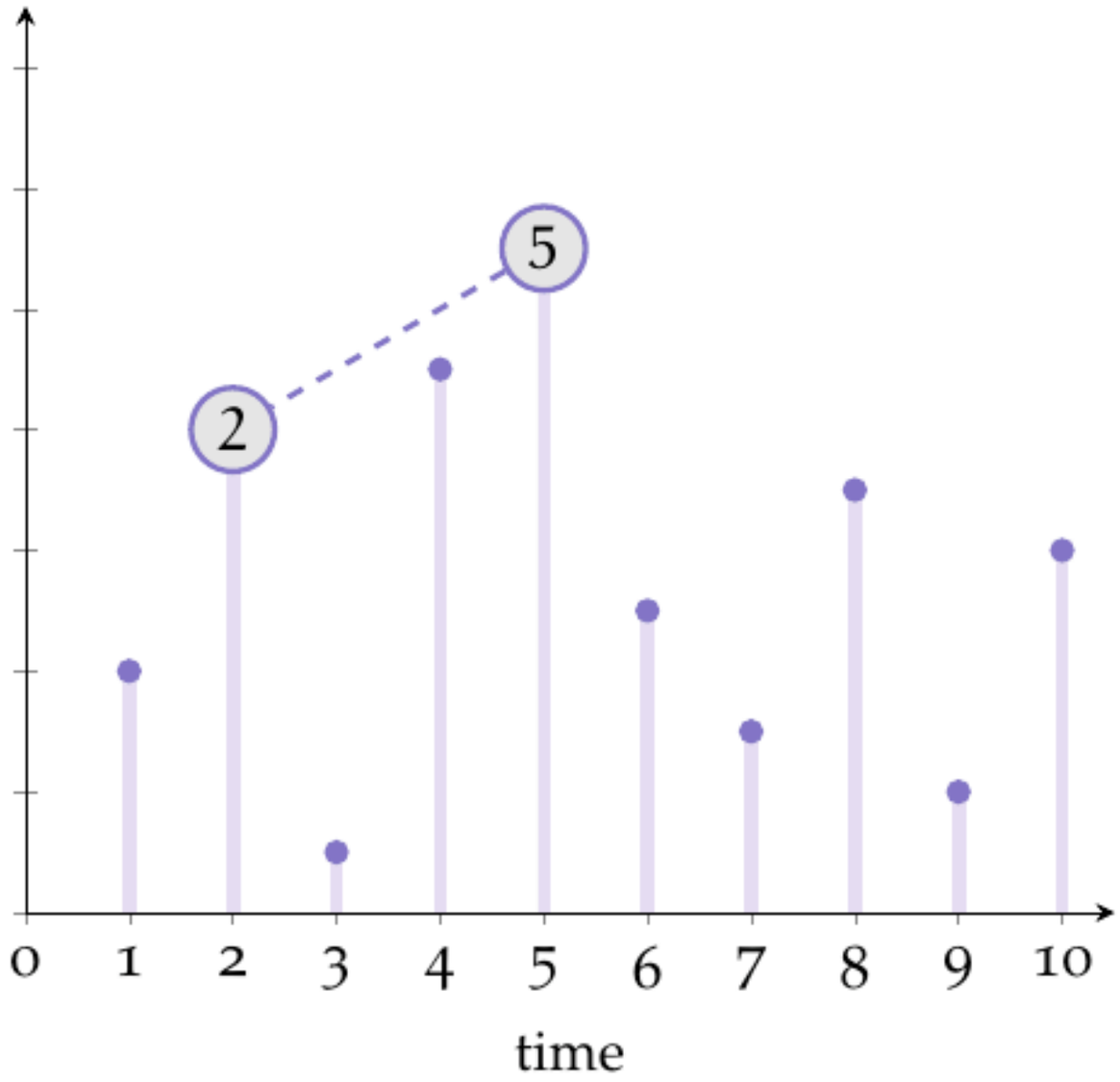
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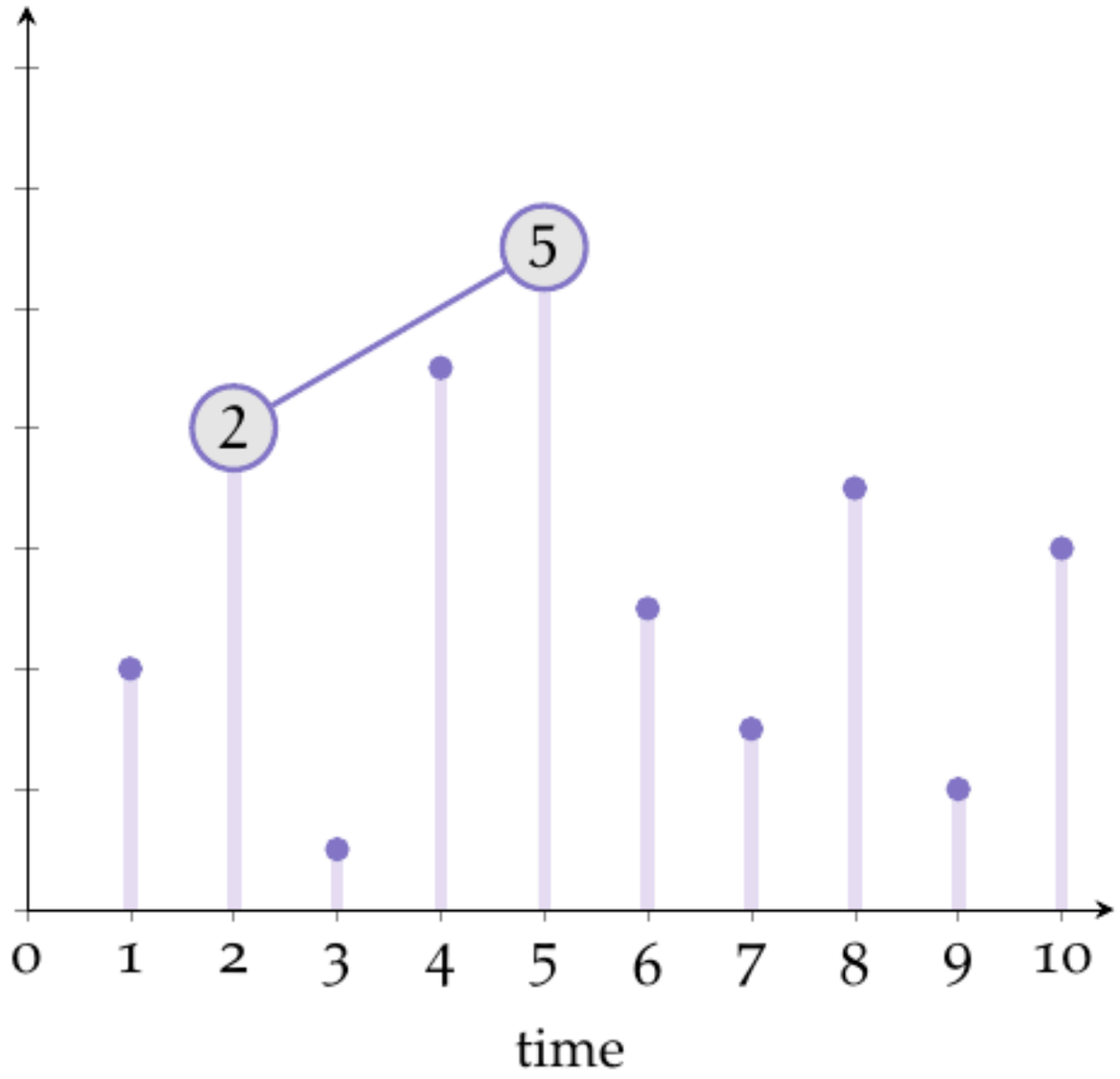
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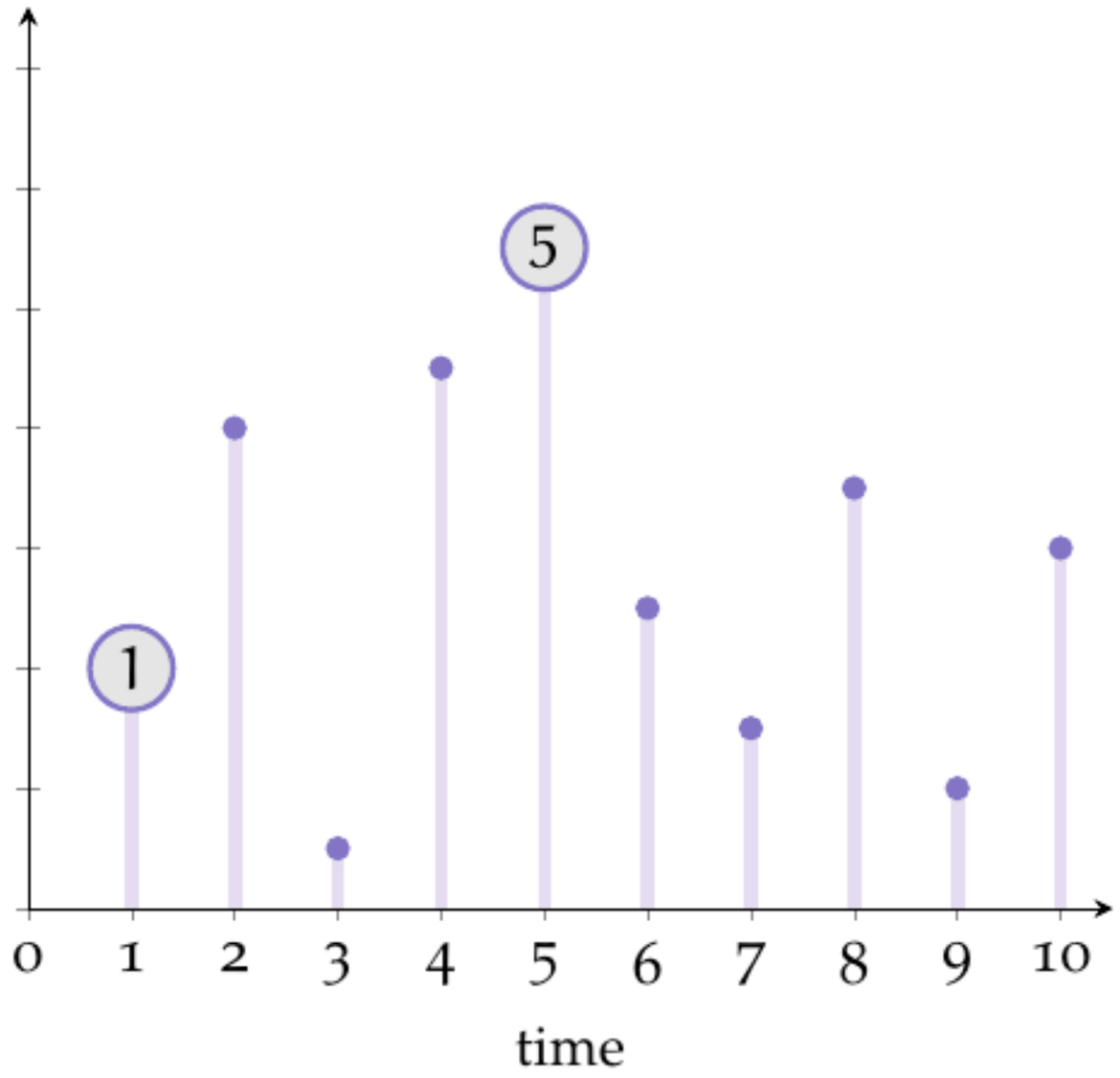
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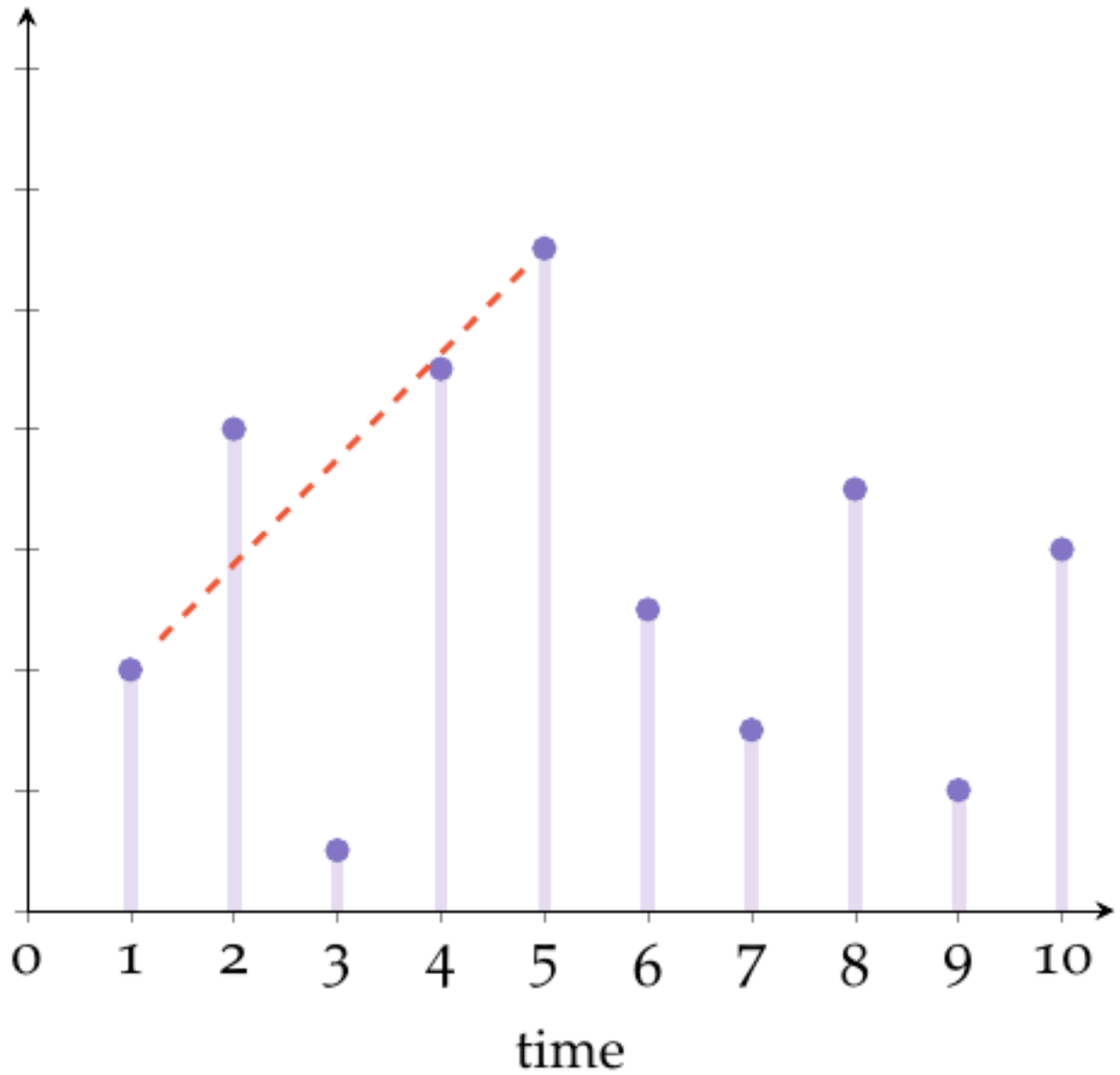
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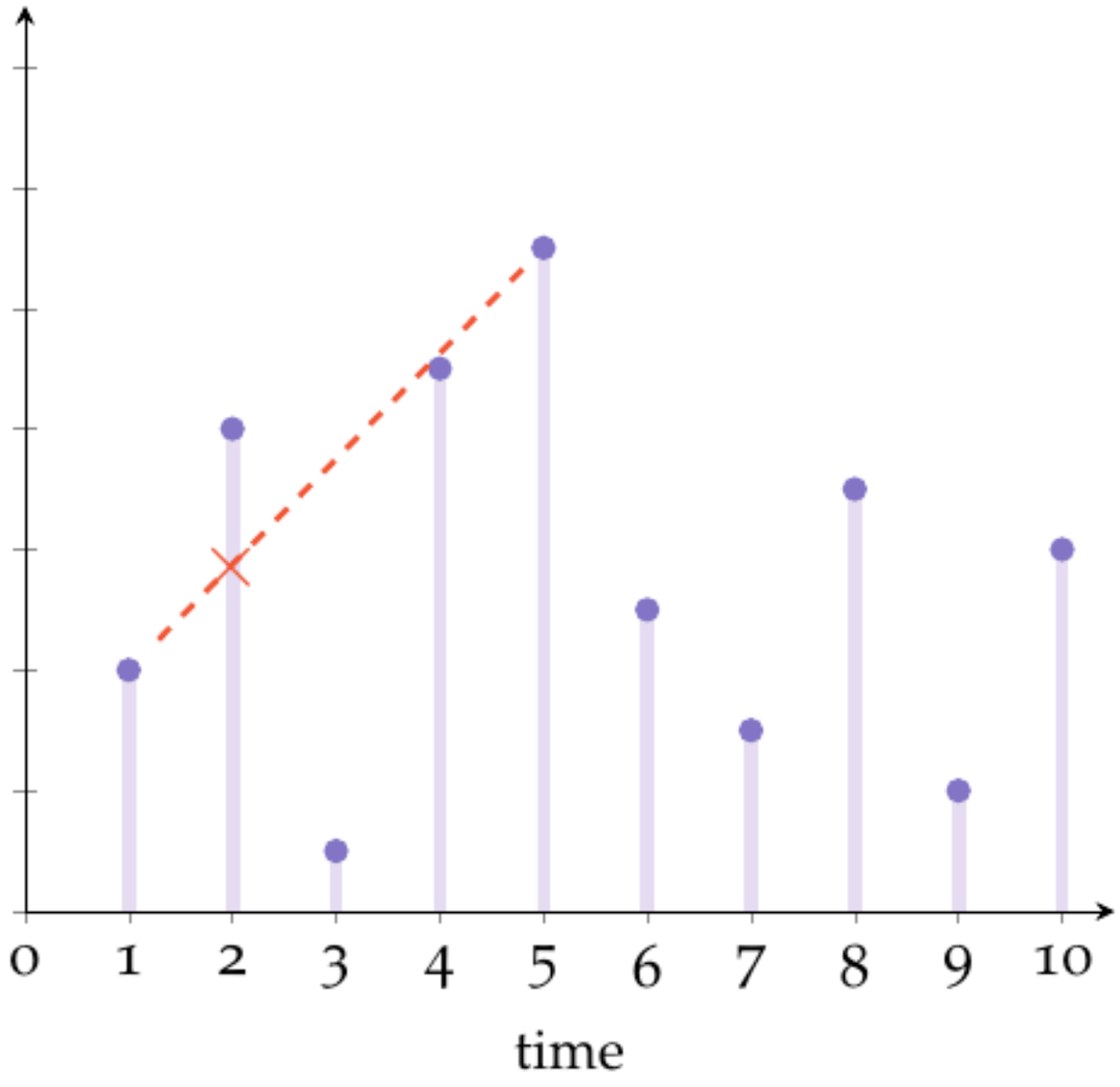
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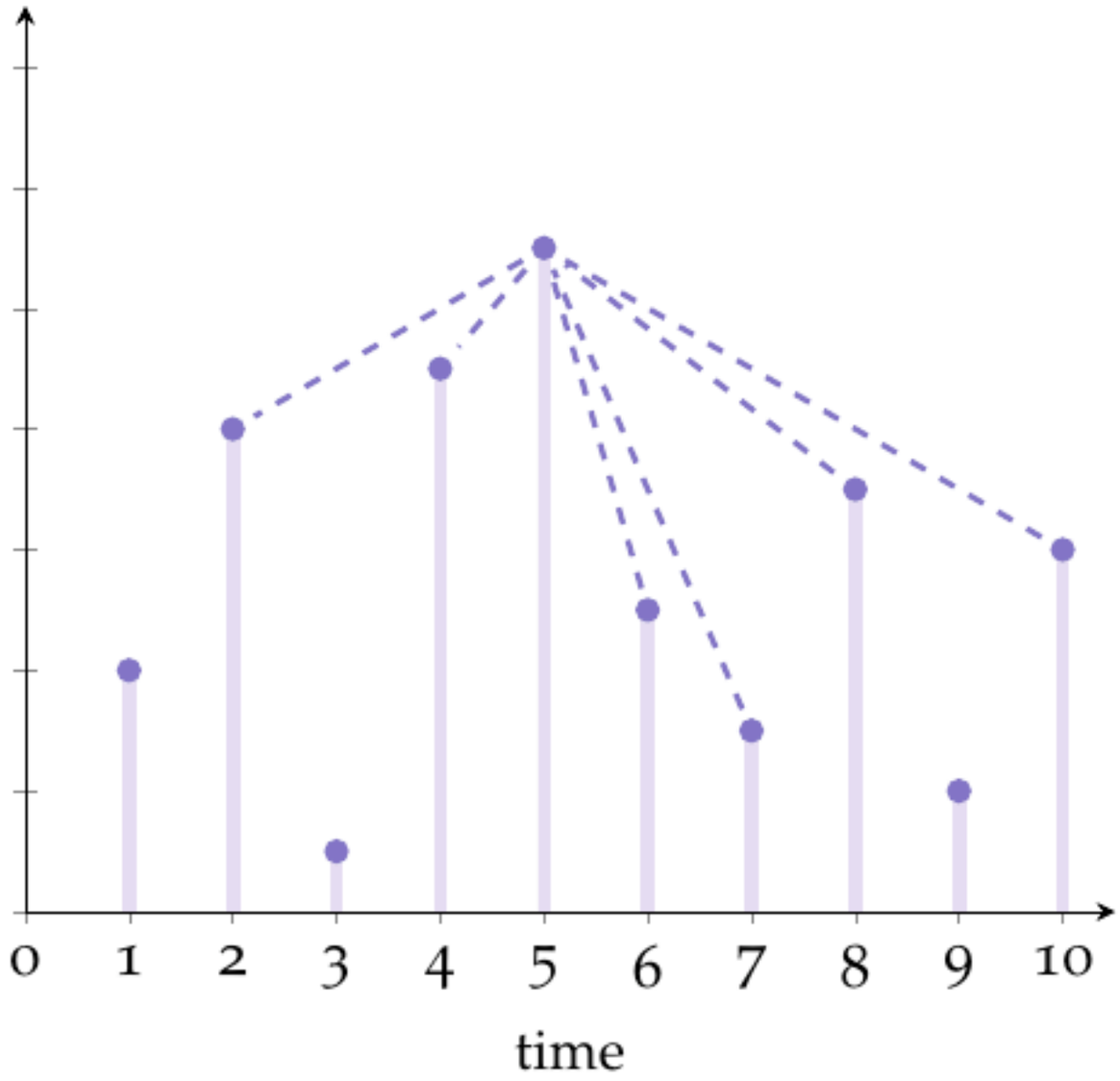
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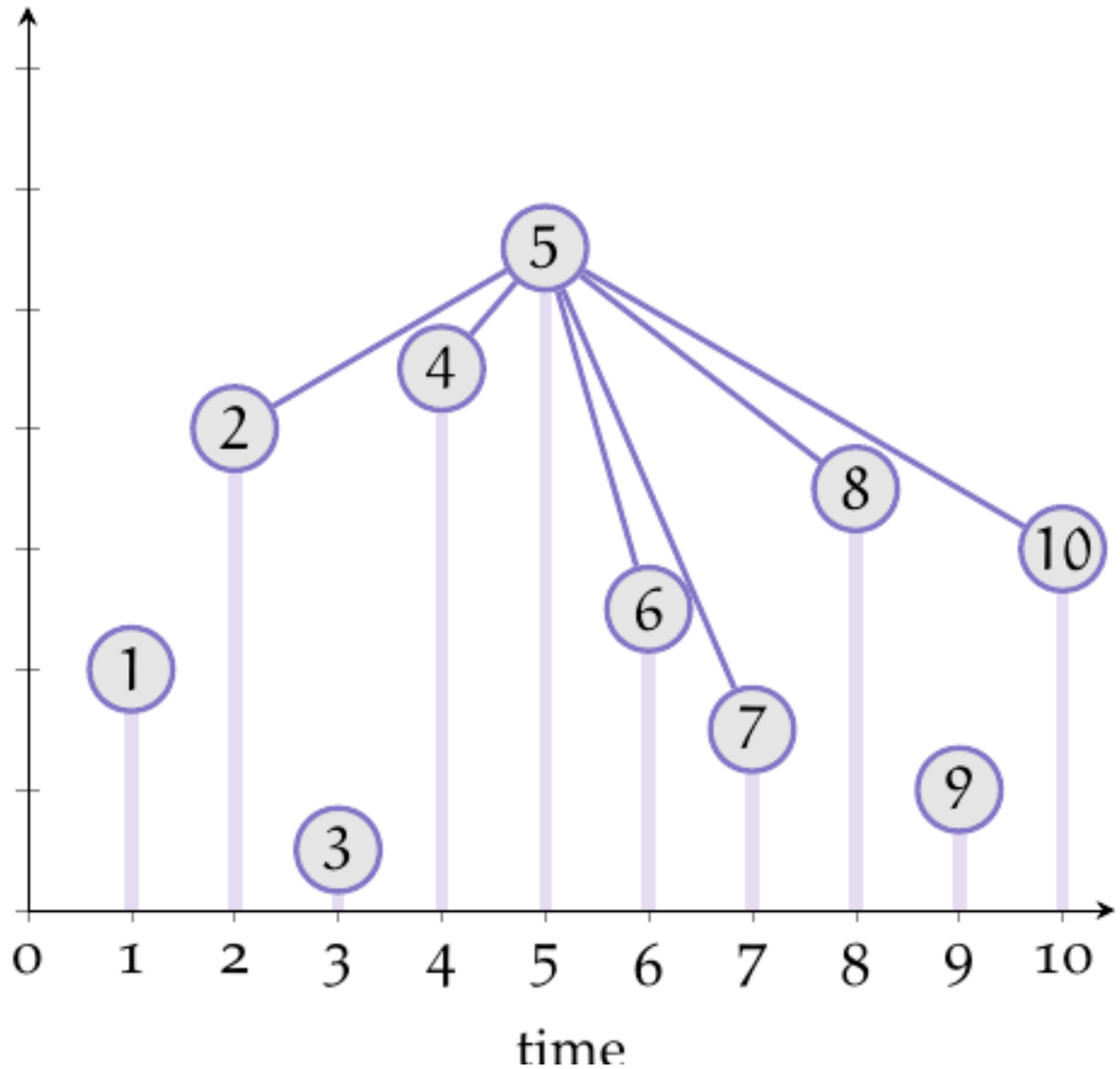
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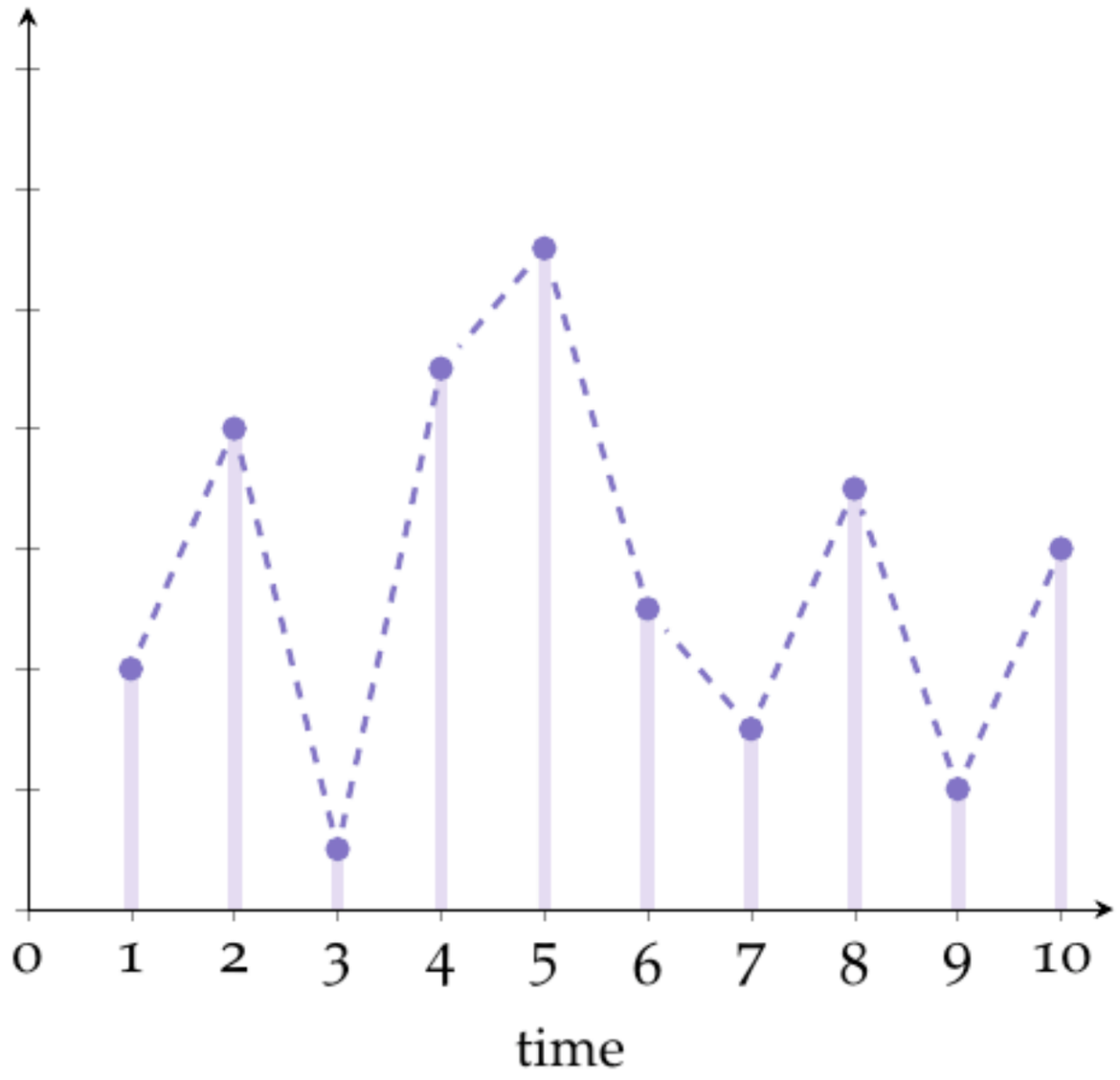
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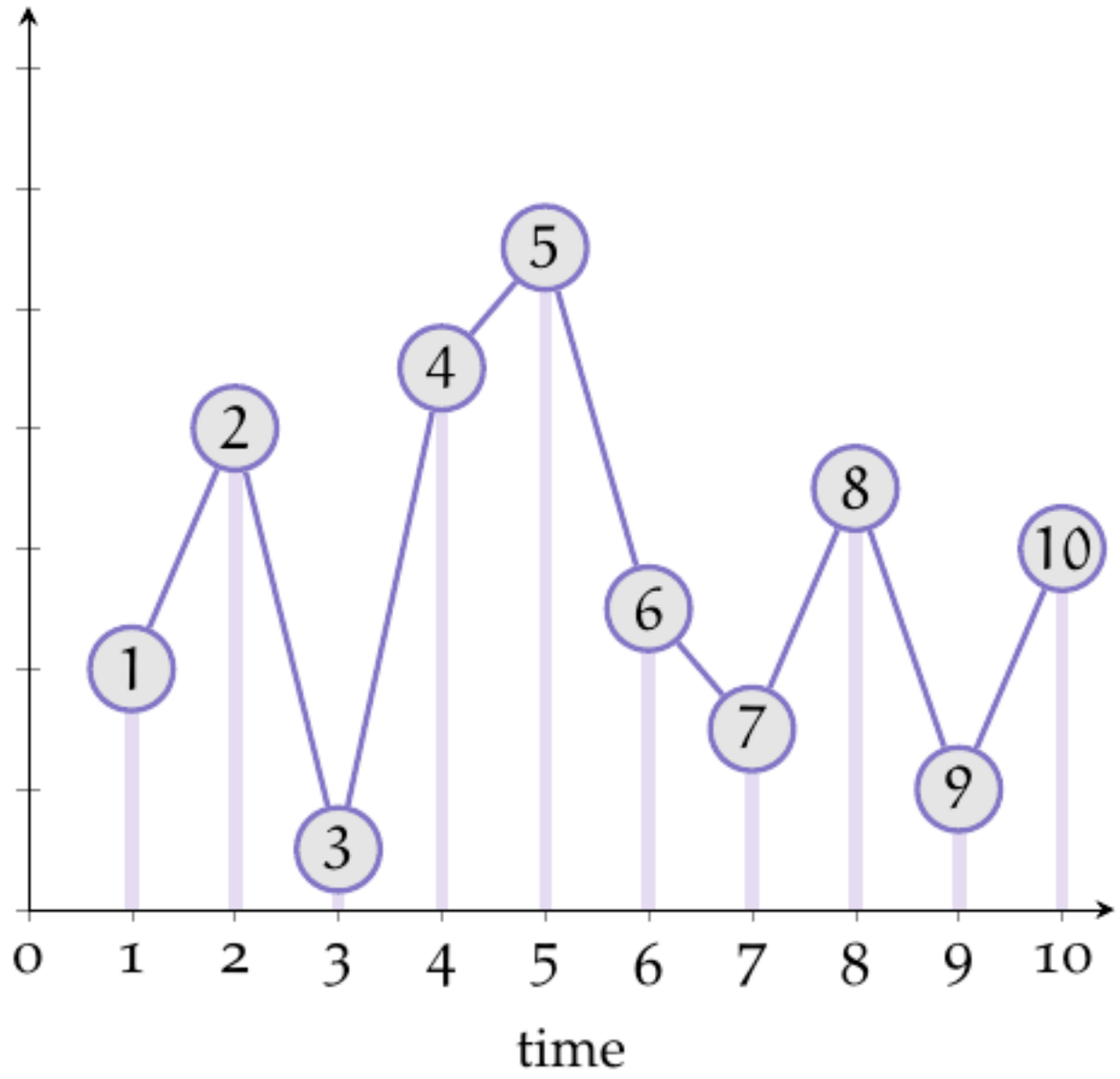
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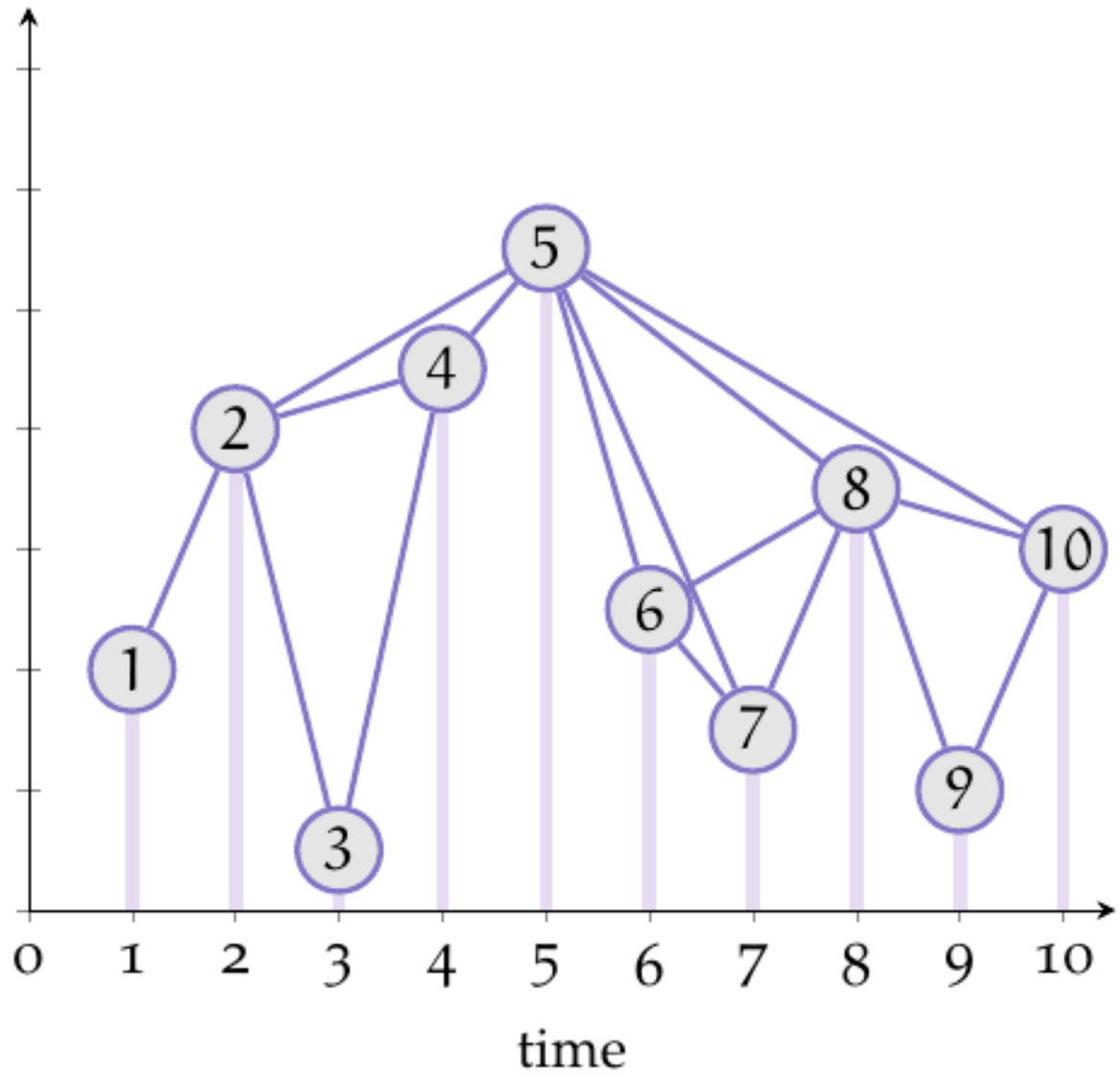
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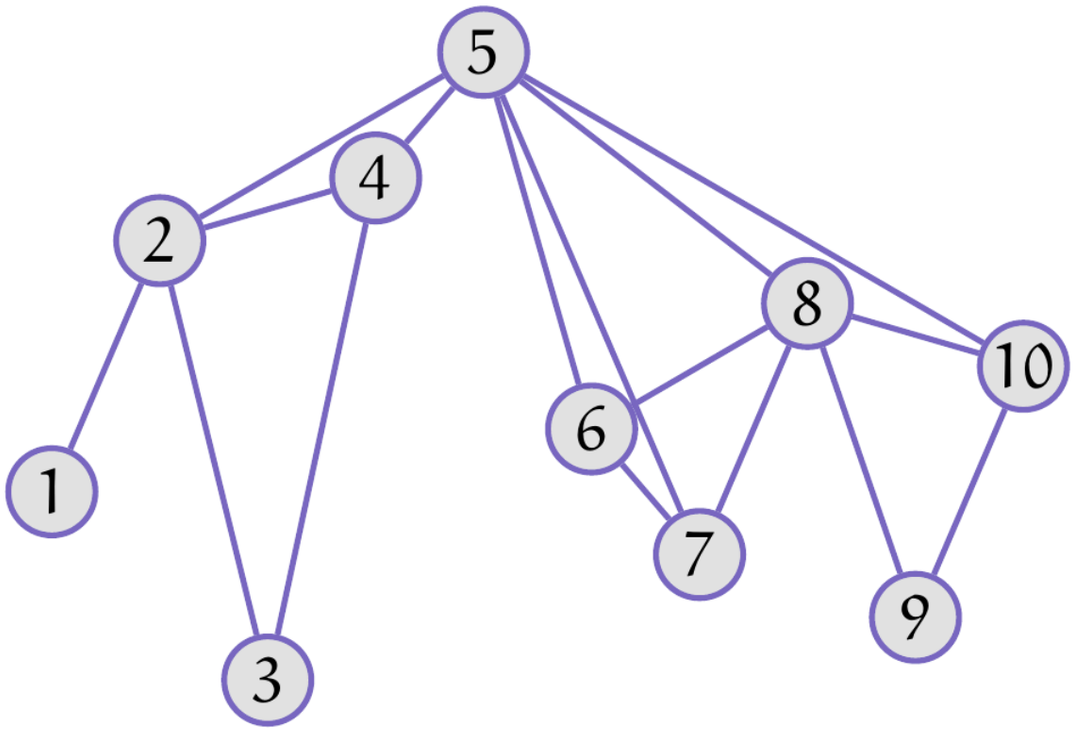
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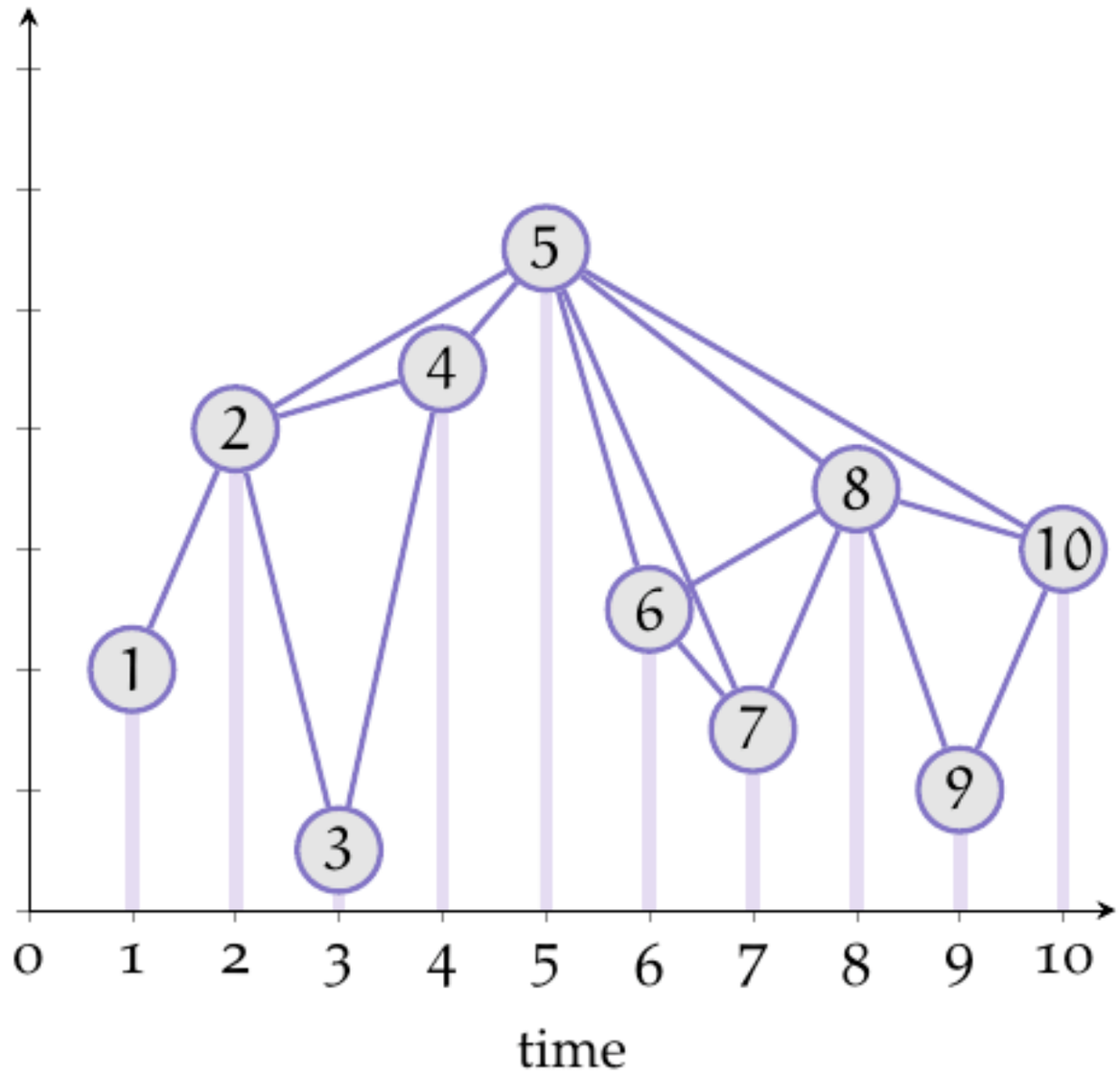
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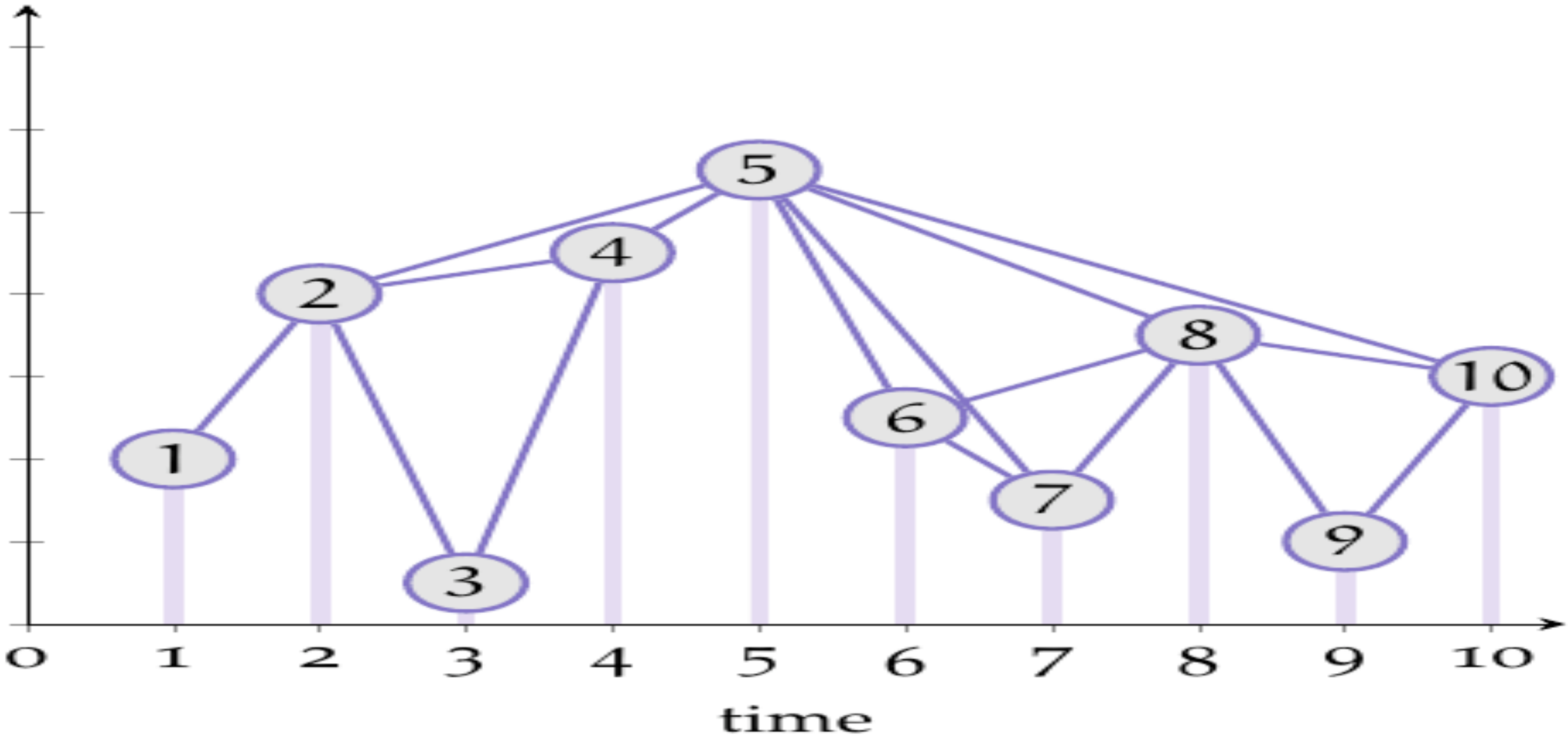
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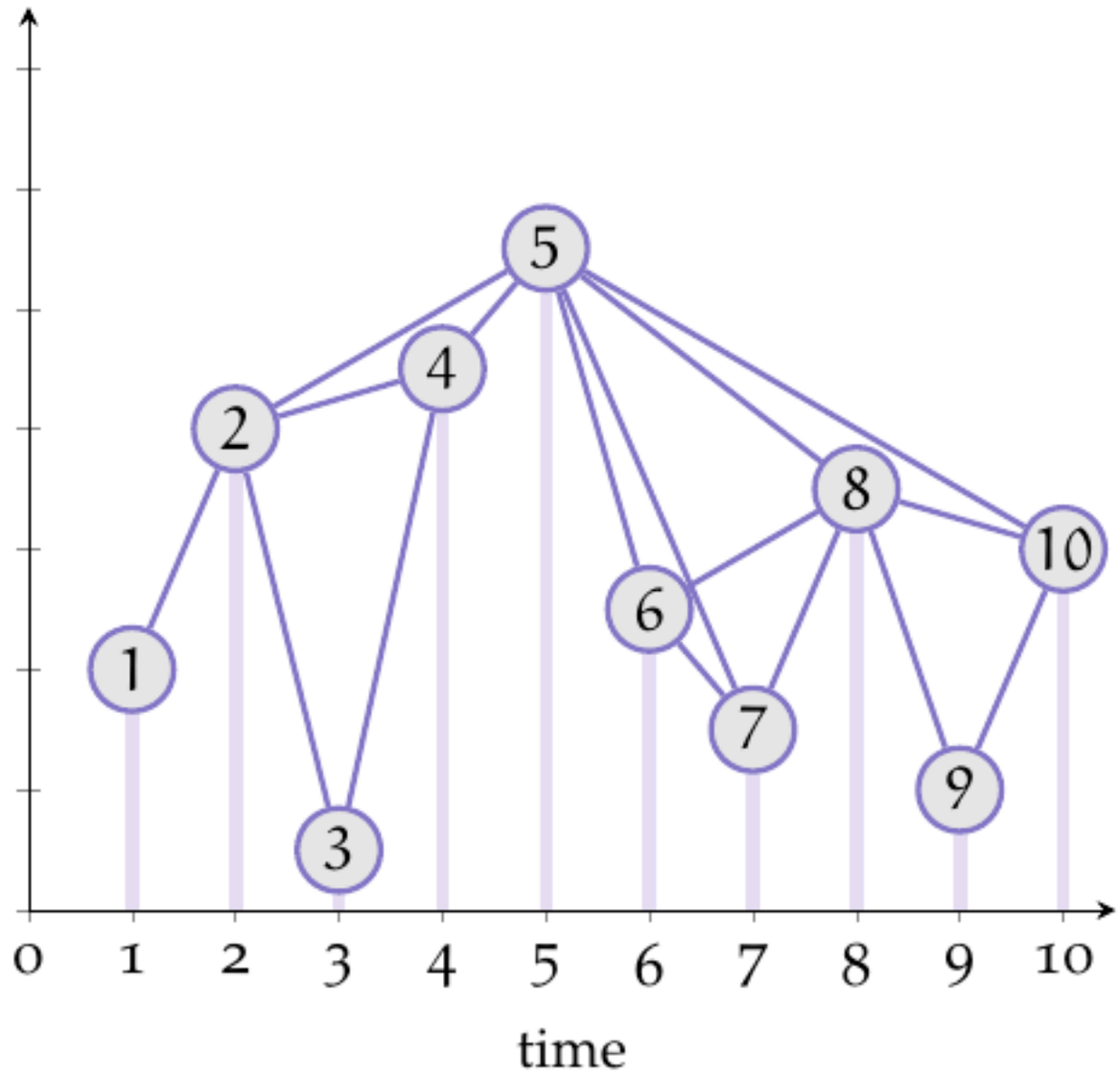
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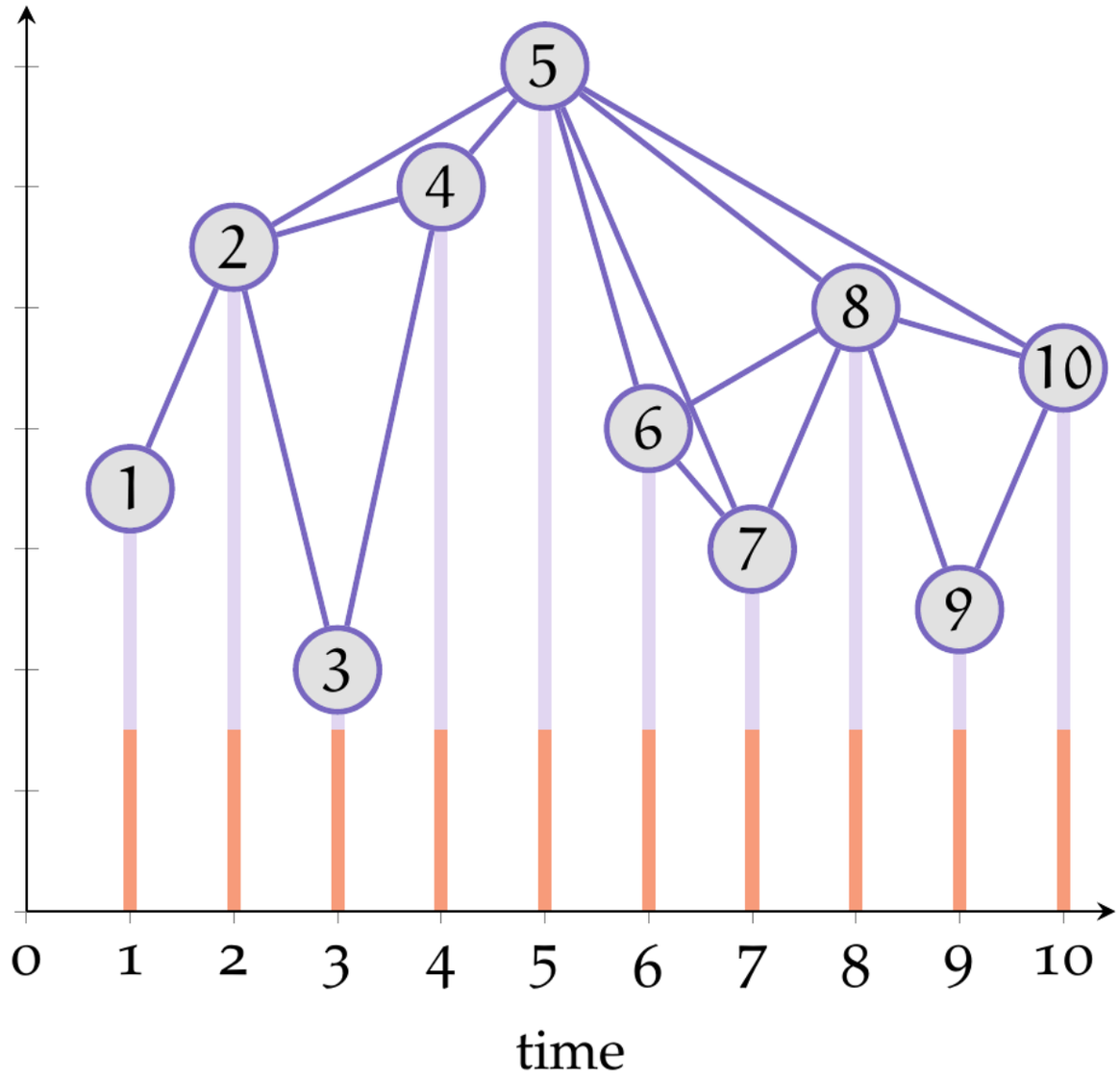
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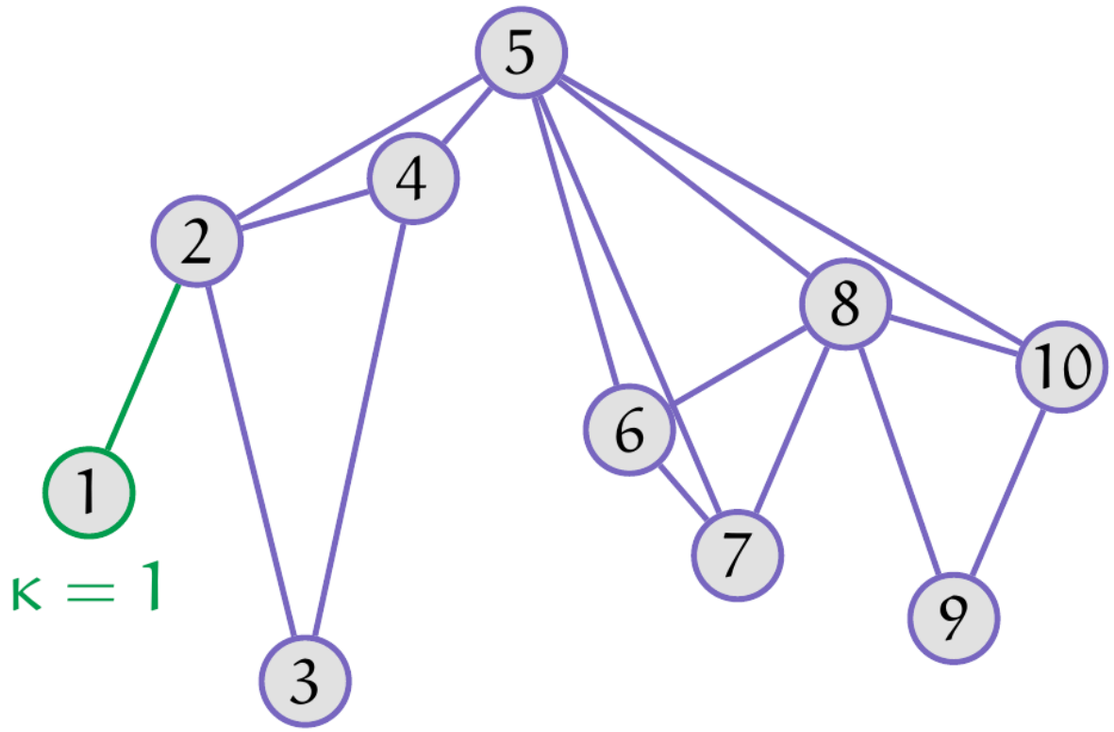
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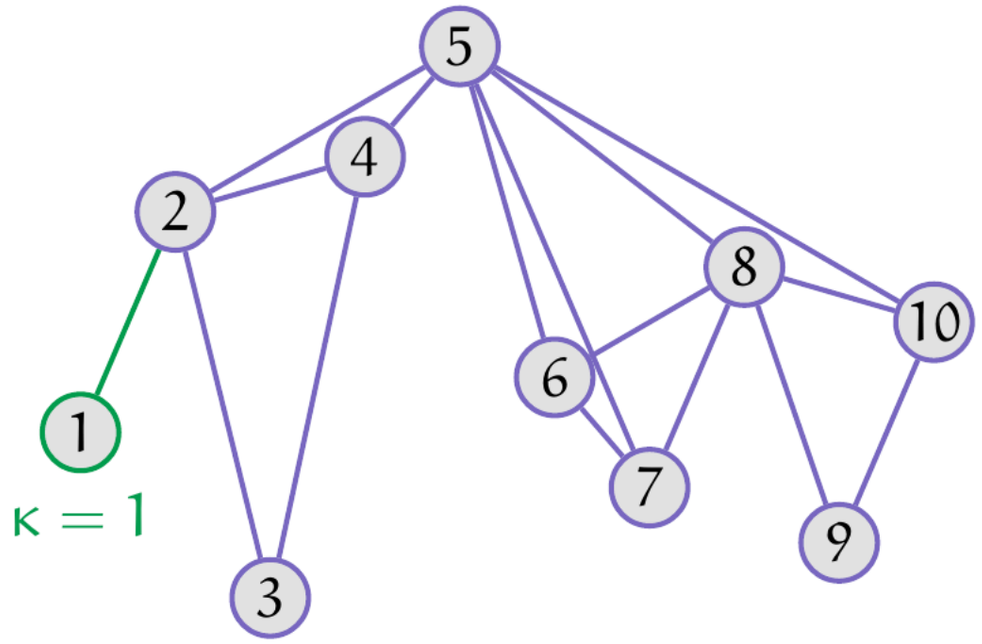
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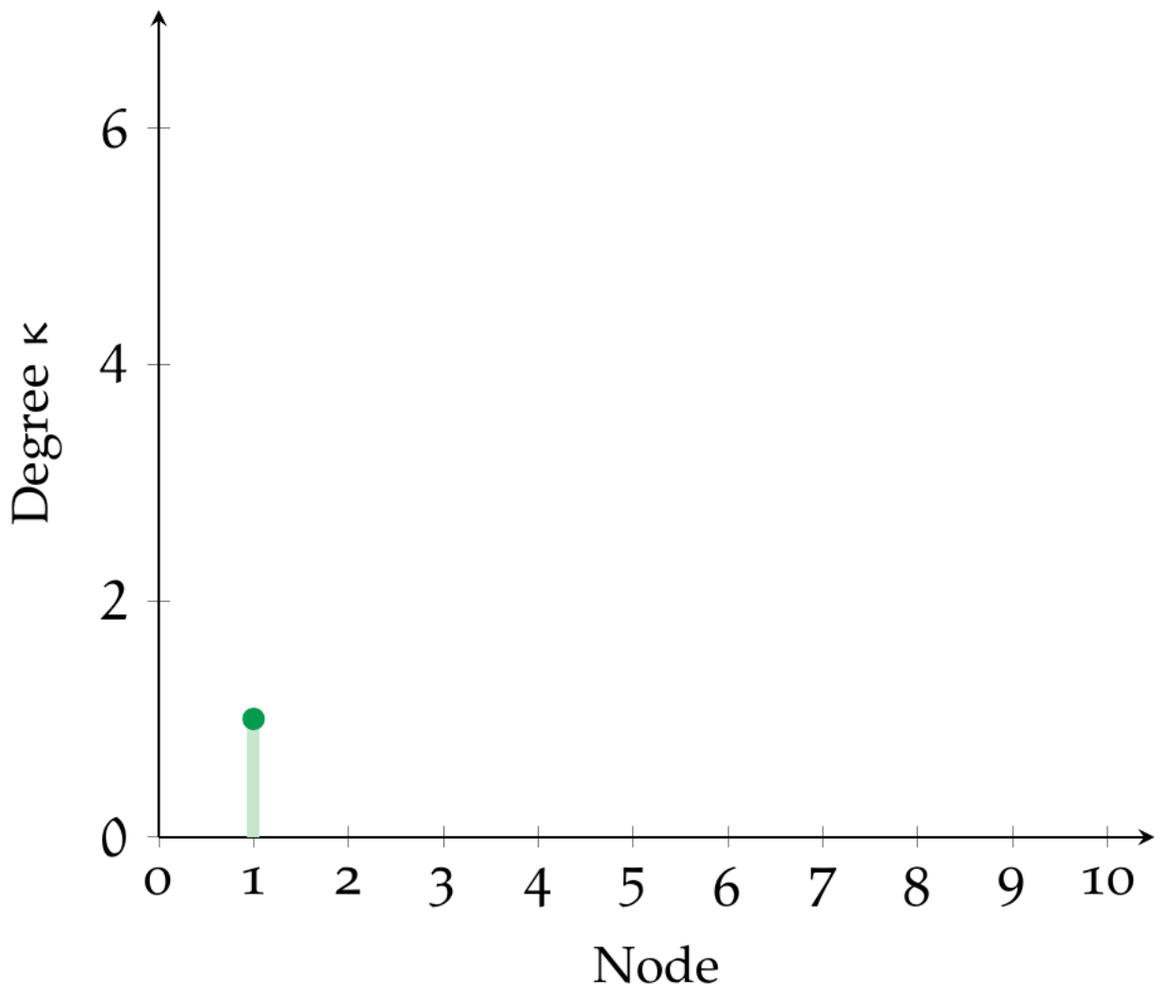
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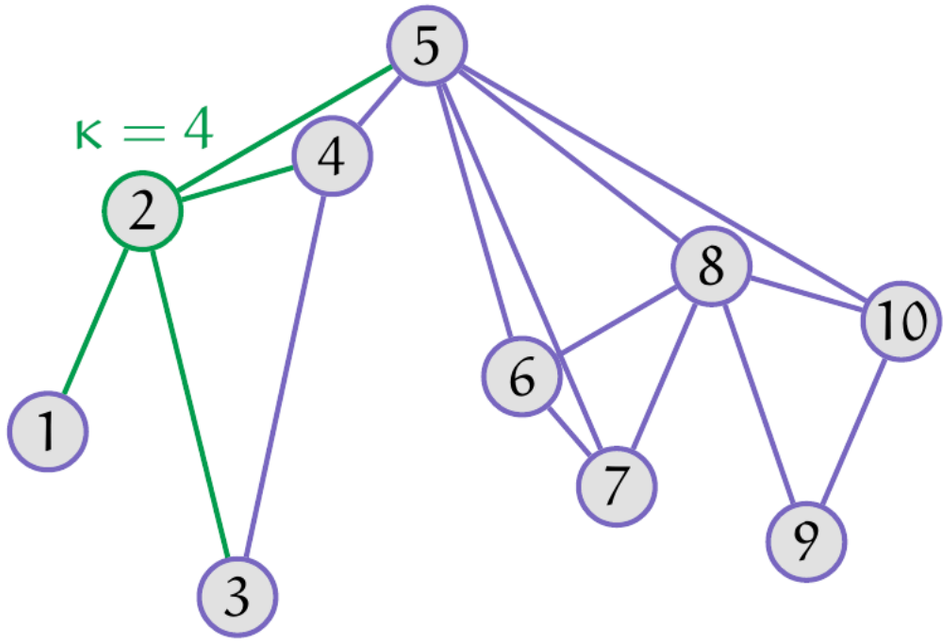
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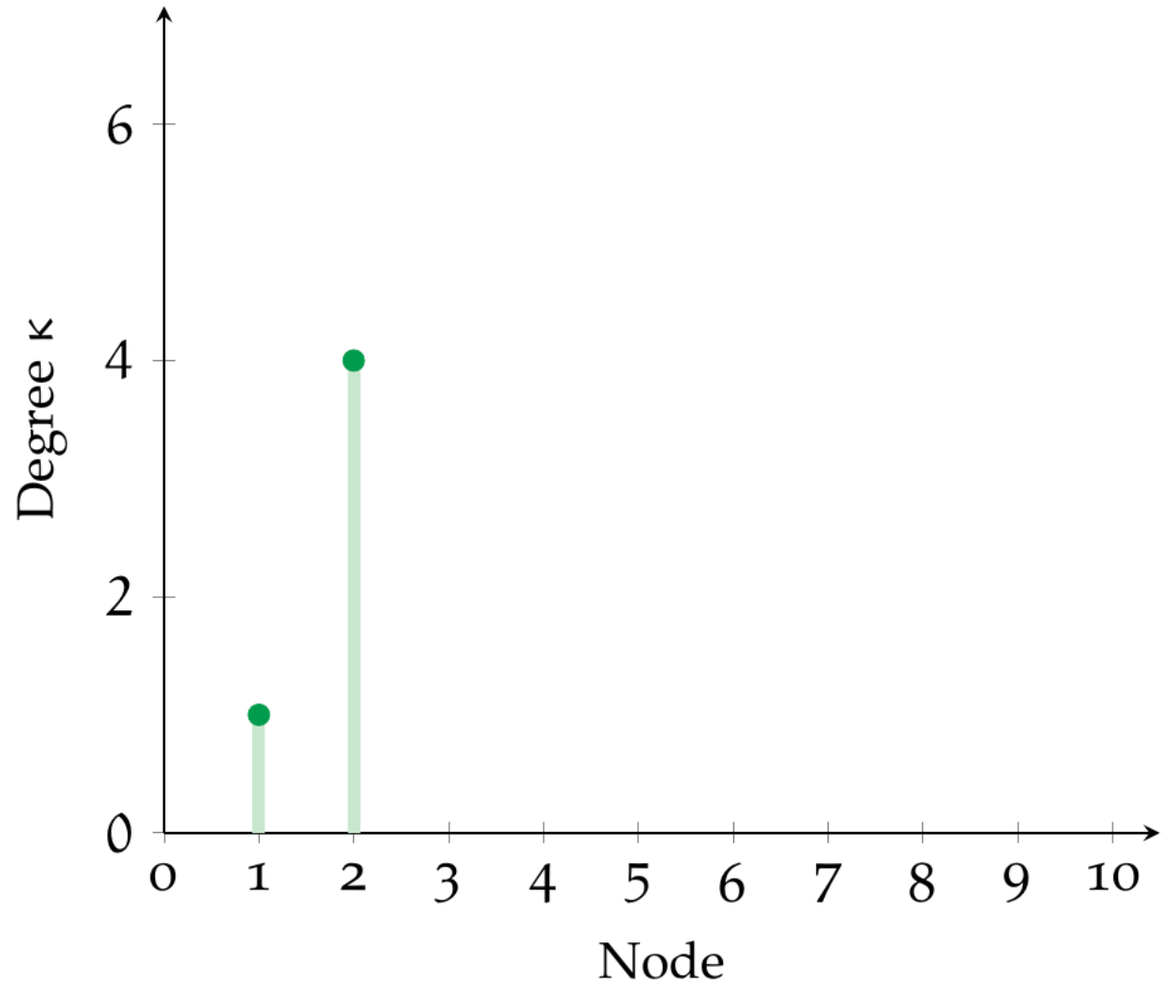
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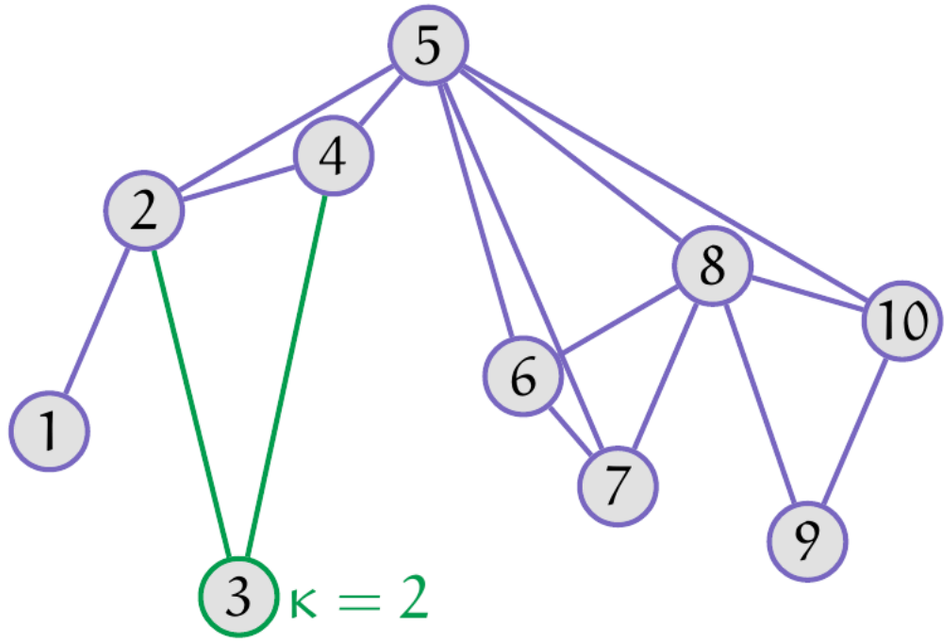
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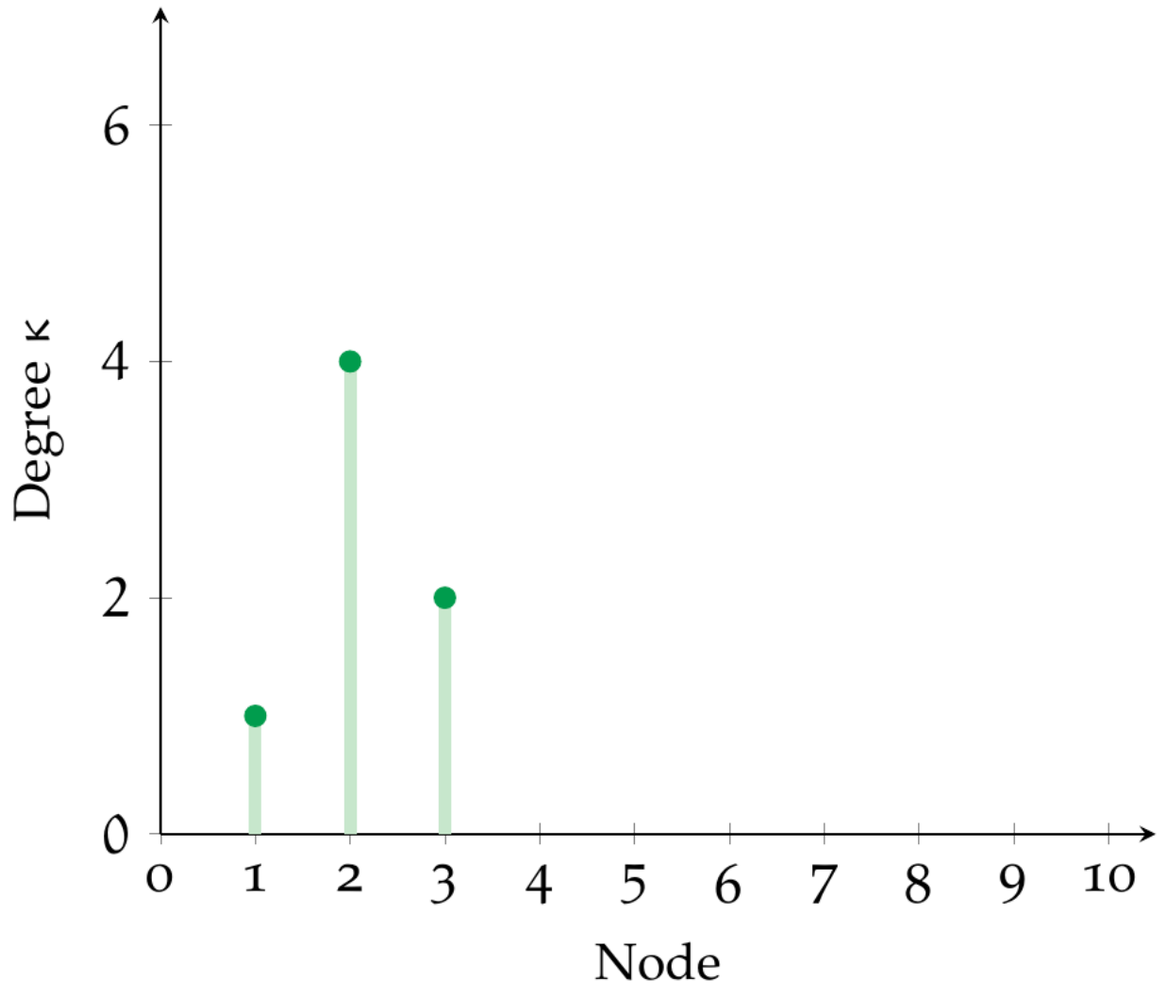
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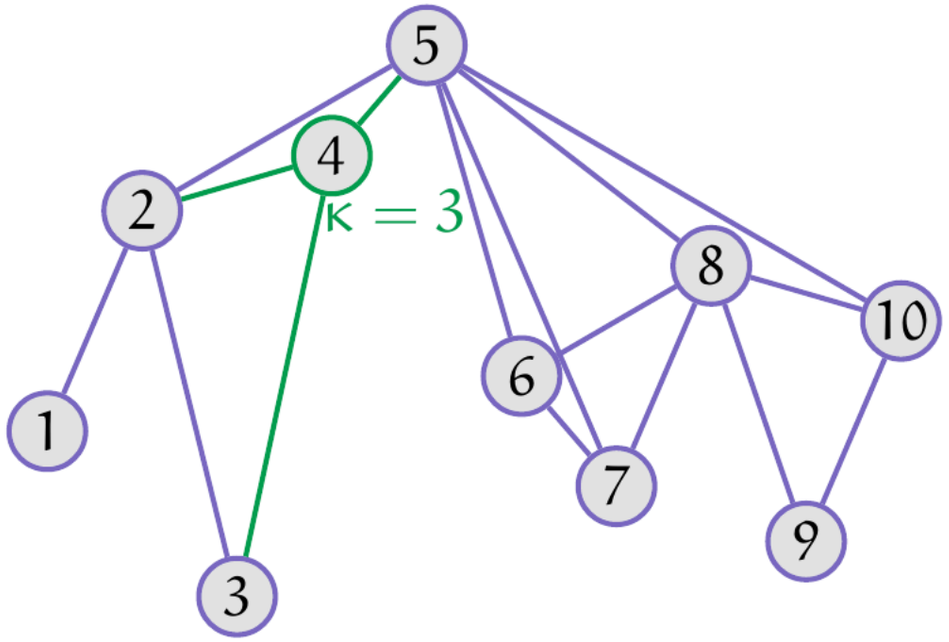
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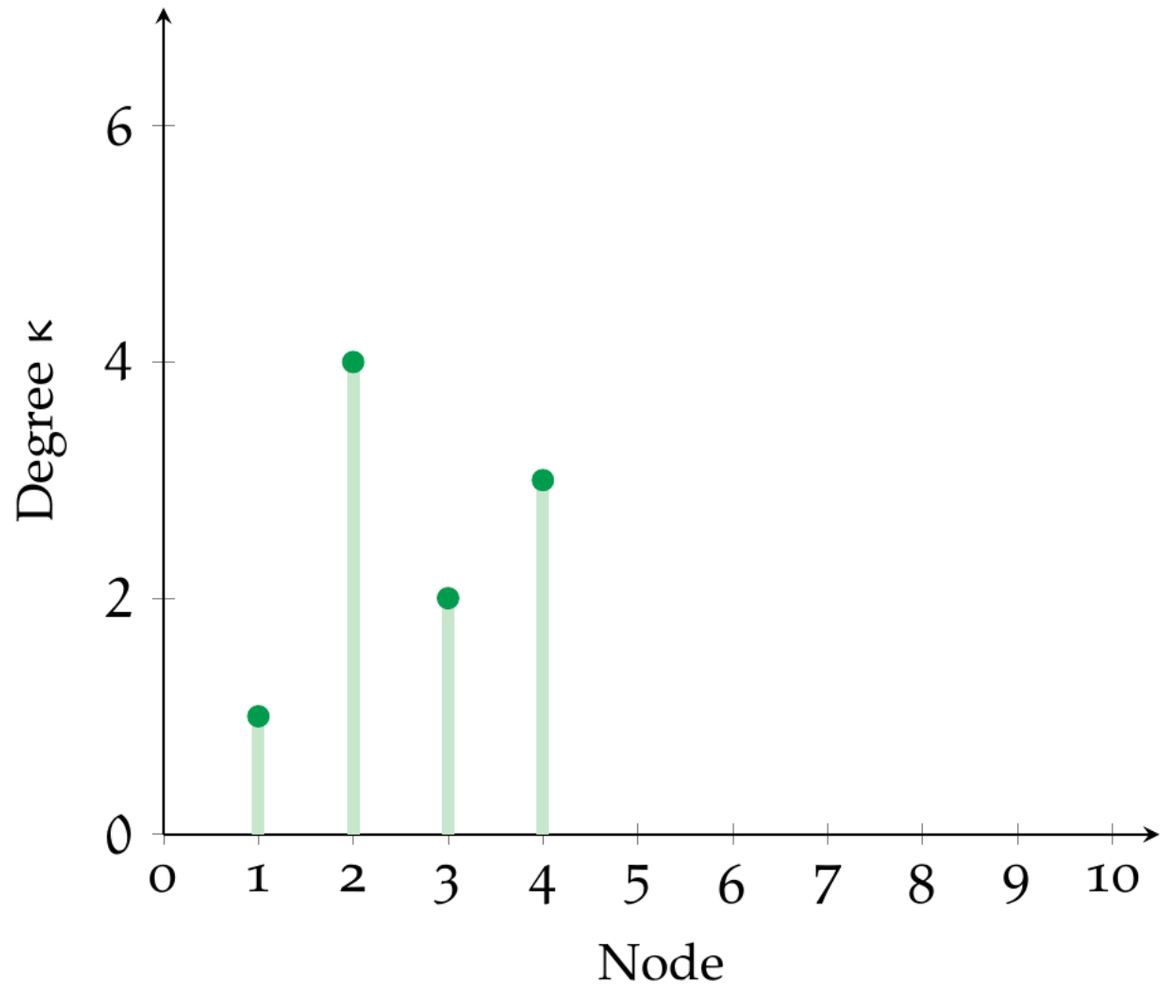
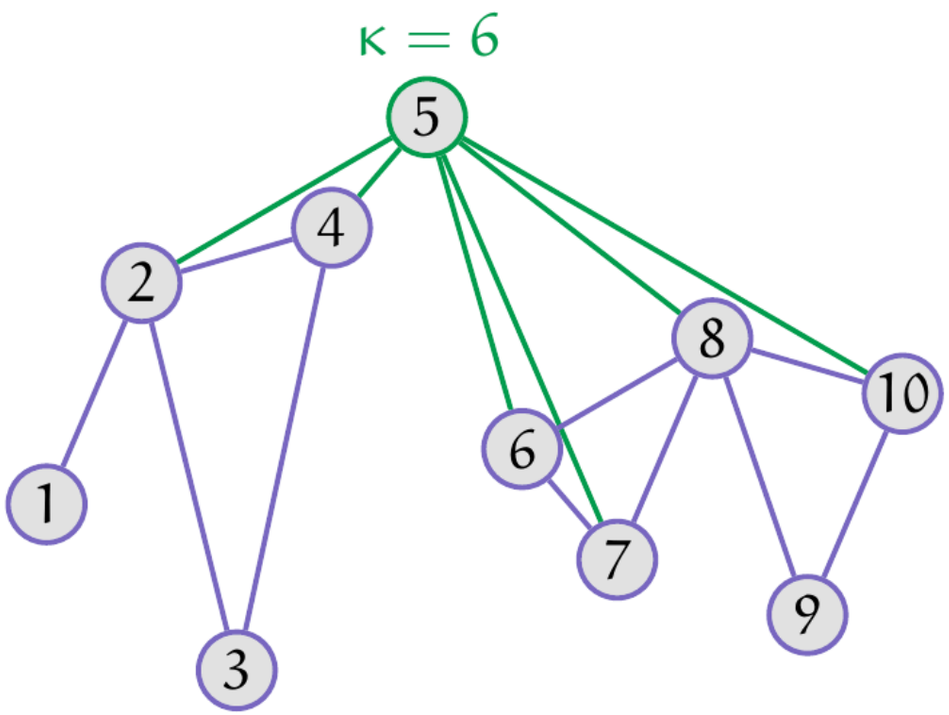
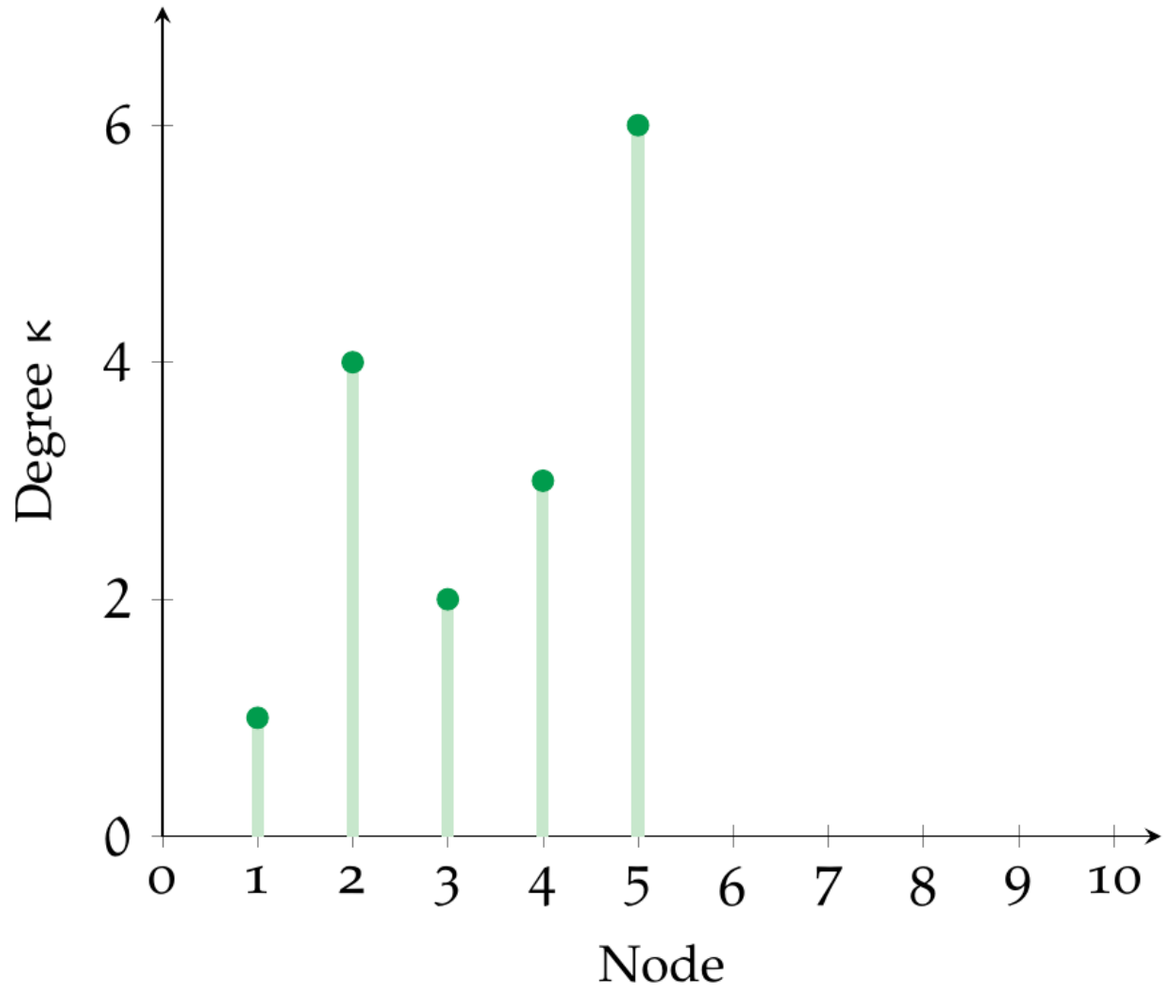
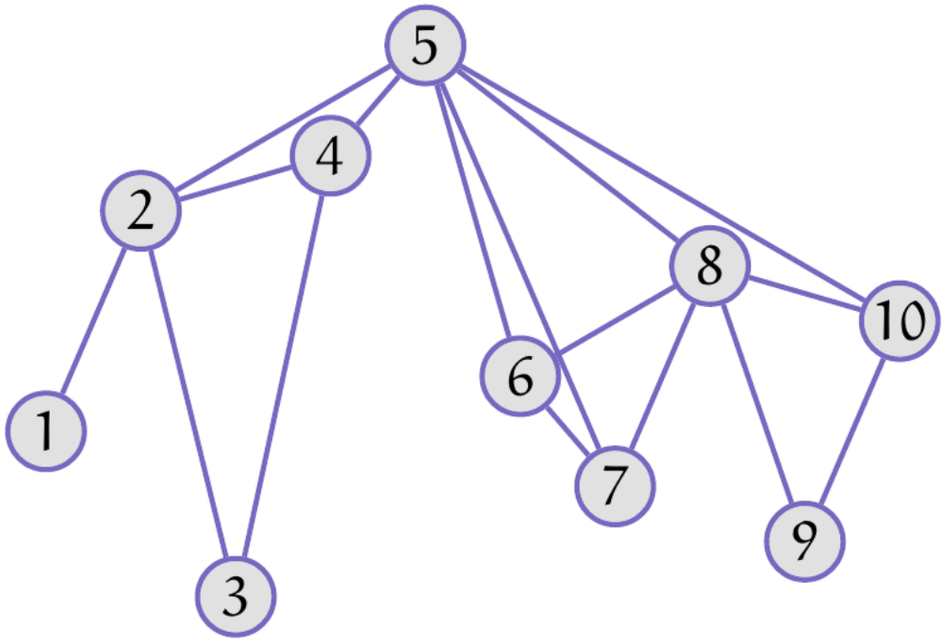
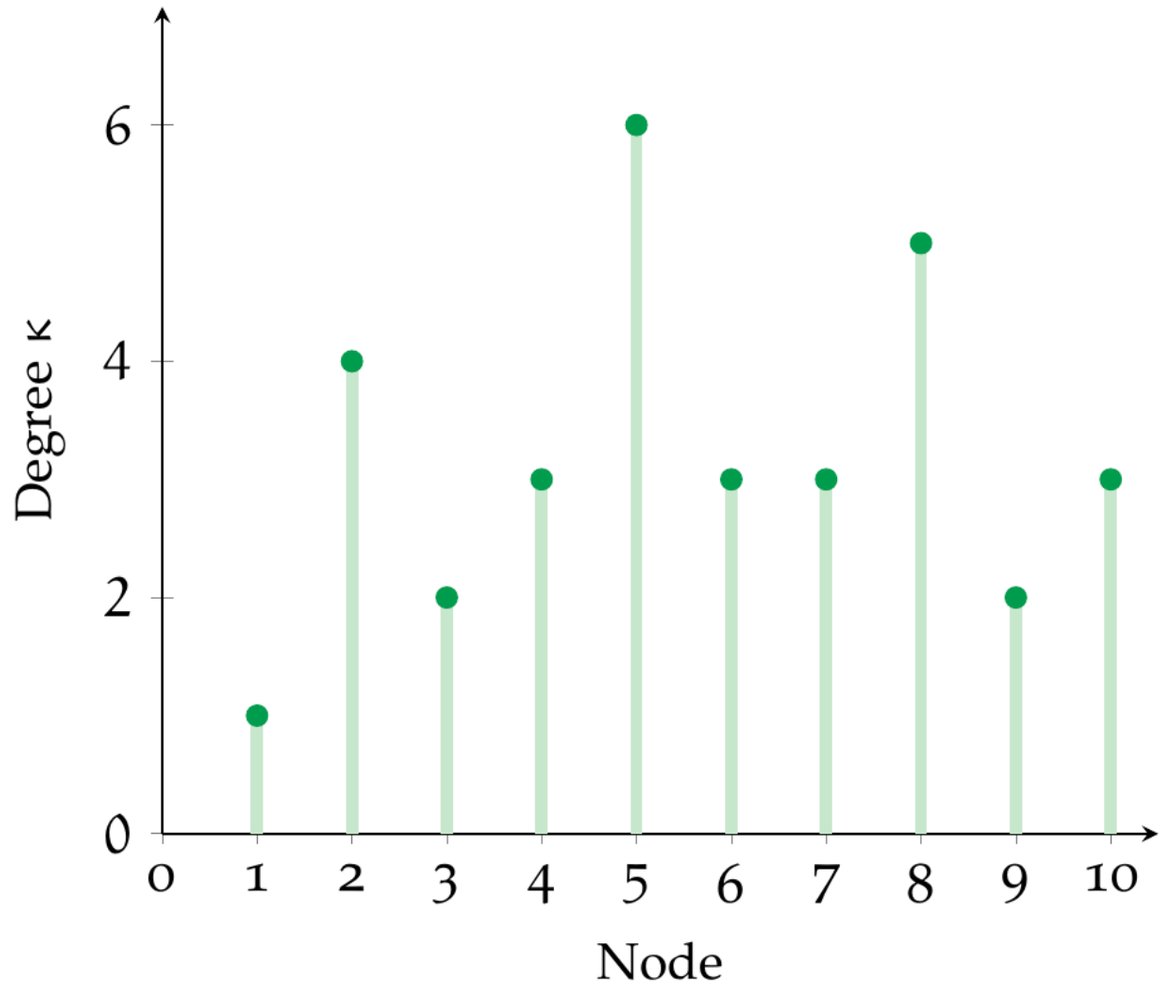
3

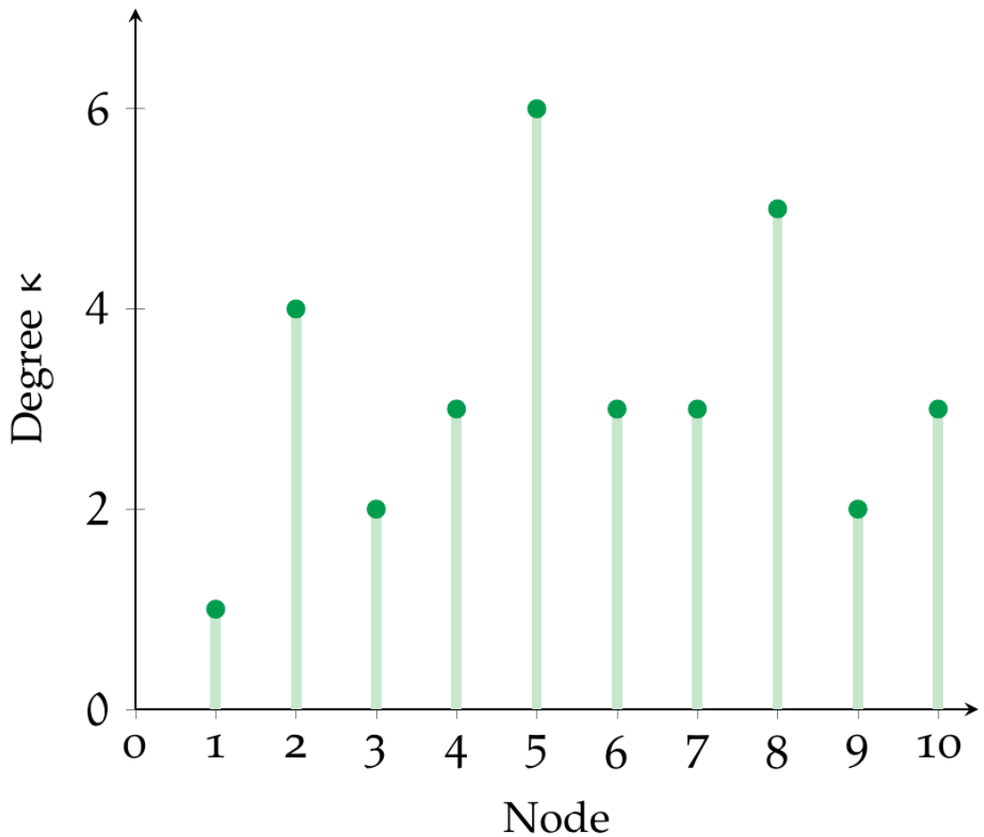

6
4
2
0
Degree κ
0
1
2
3
4
5
6
7
8
9
10
Node

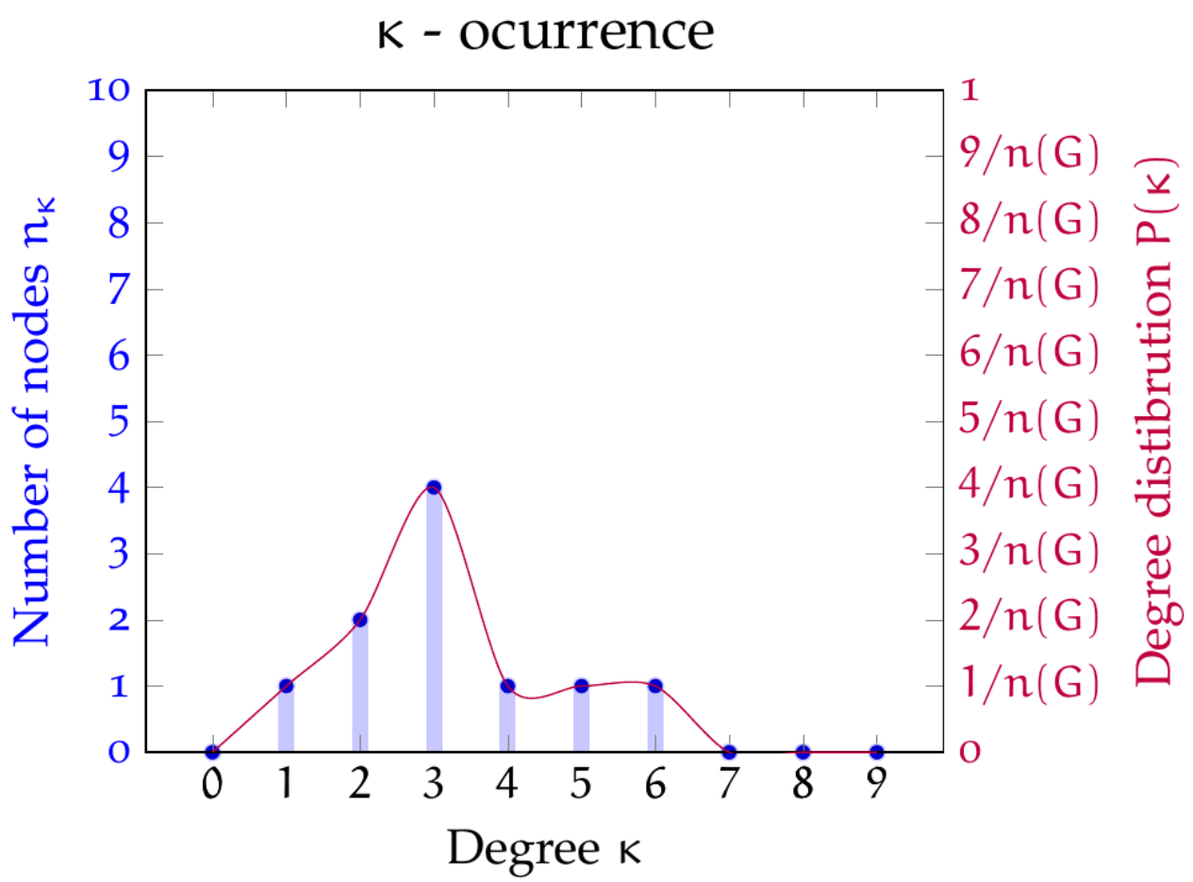

κ = 6
5
4
2
8
10
6
1
7
9
3


Degree κ
0
2
4
6
0
1
2
3
4
5
6
7
8
9
10
Node

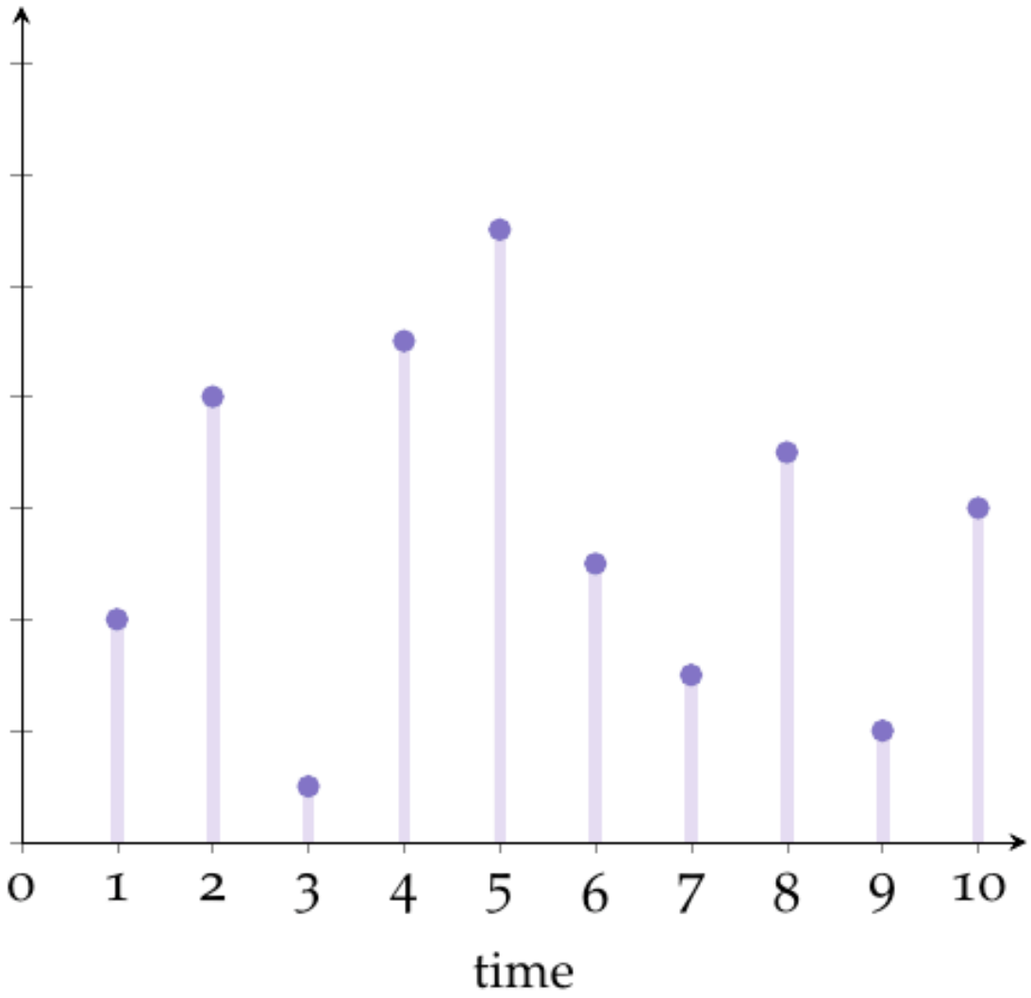

5
4
2
8
10
6
1
7
9
3

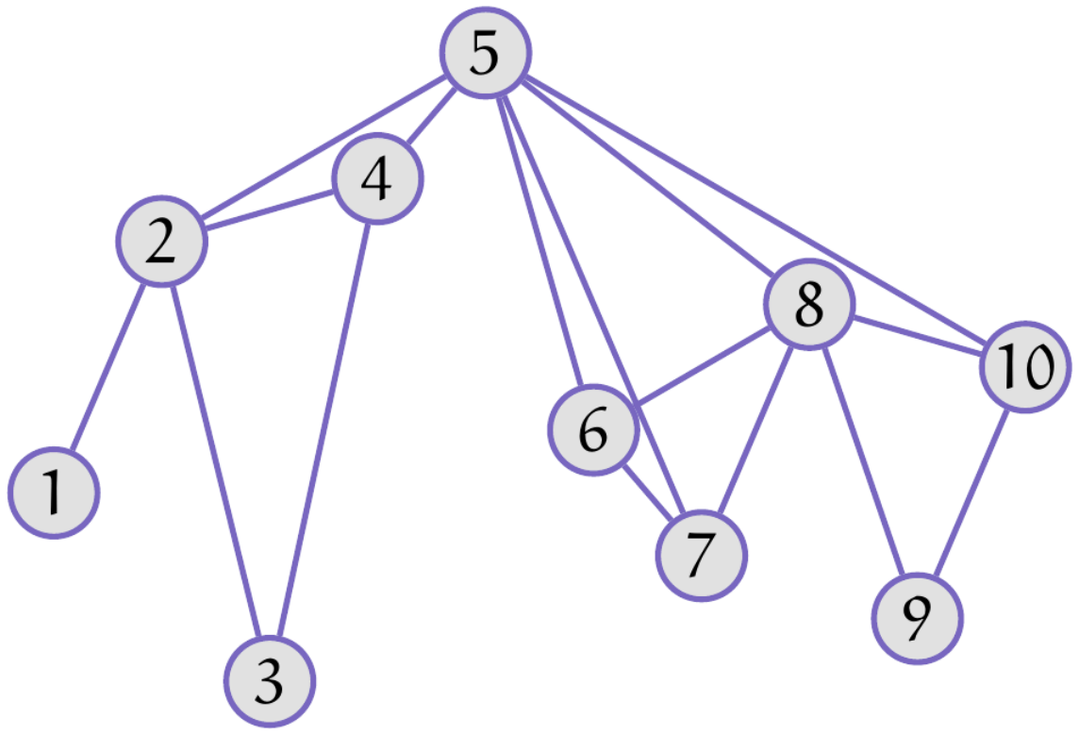

Degree κ
0
2
4
6
0
1
2
3
4
5
6
7
8
9
10
Node


Degree κ
0
2
4
6
0 1 2 3 4 5 6 7 8 9 10
Node

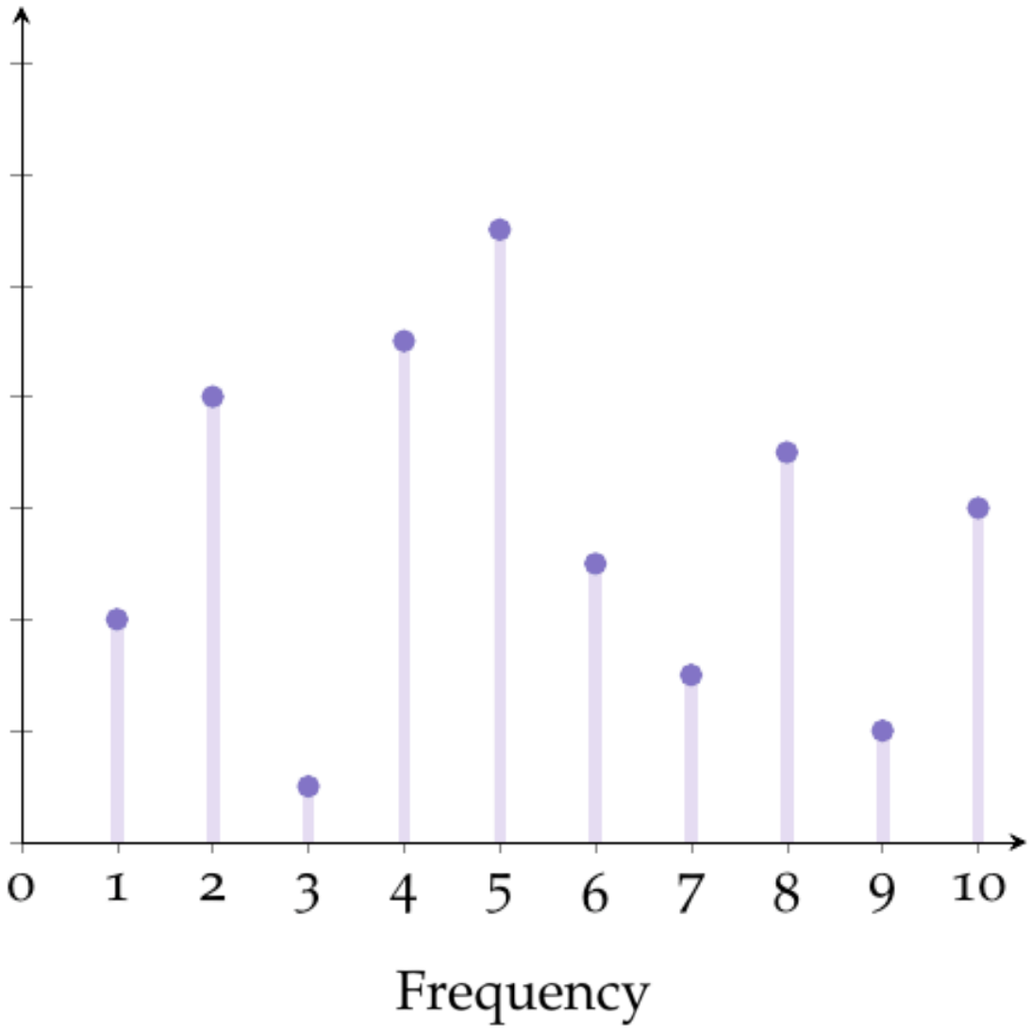

κ - ocurrence
Number of nodes n_κ
Degree distribution P(κ)
0 1 2 3 4 5 6 7 8 9 10
1
9/n(G)
8/n(G)
7/n(G)
6/n(G)
5/n(G)
4/n(G)
3/n(G)
2/n(G)
1/n(G)
0
0 1 2 3 4 5 6 7 8 9
Degree κ

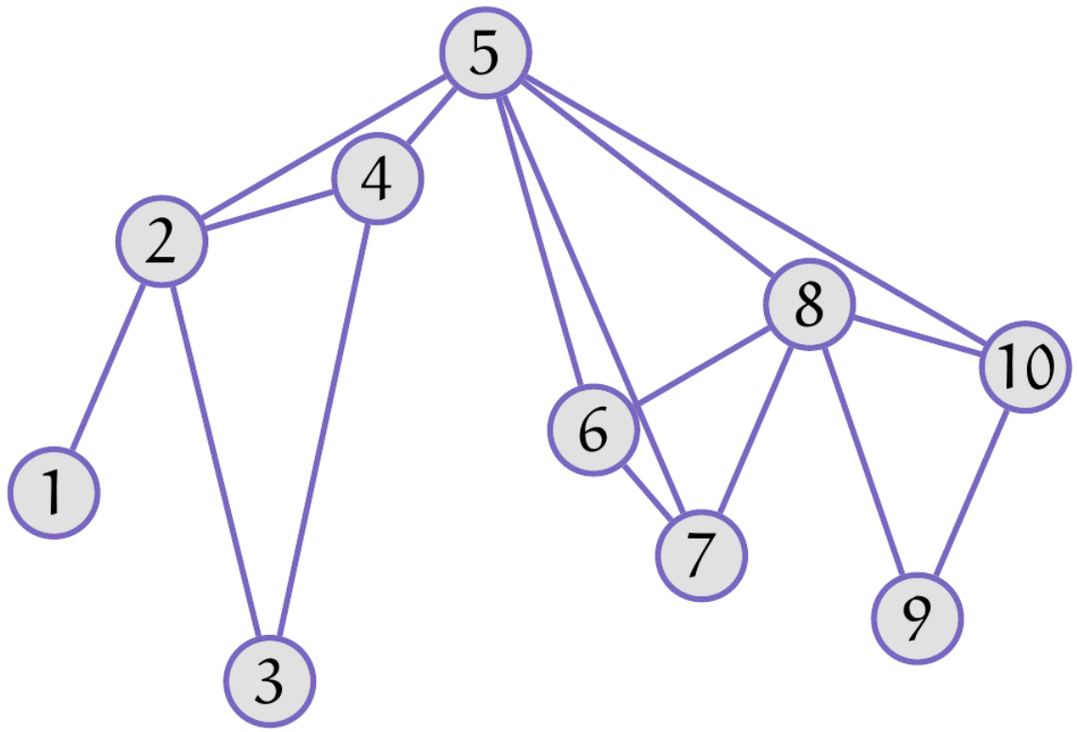
SPECTRAL VISIBILITY GRAPHS

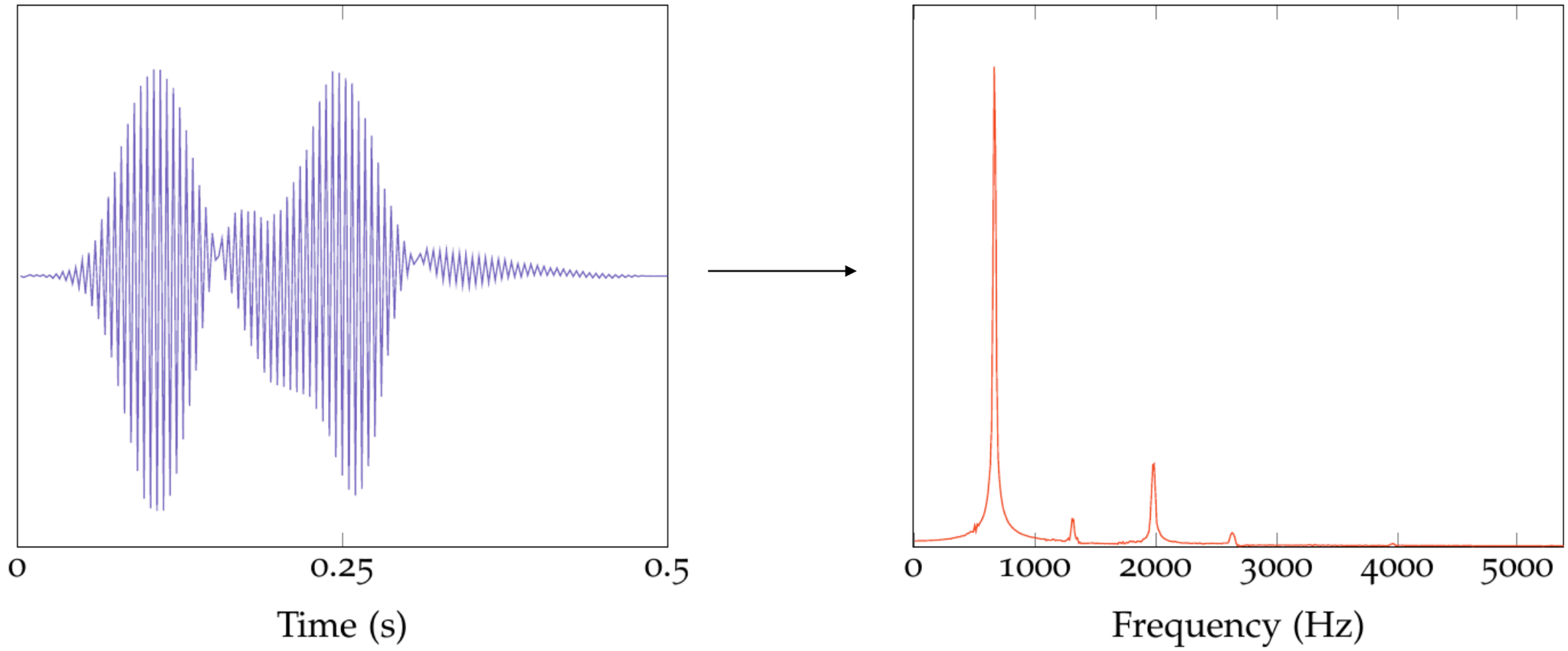


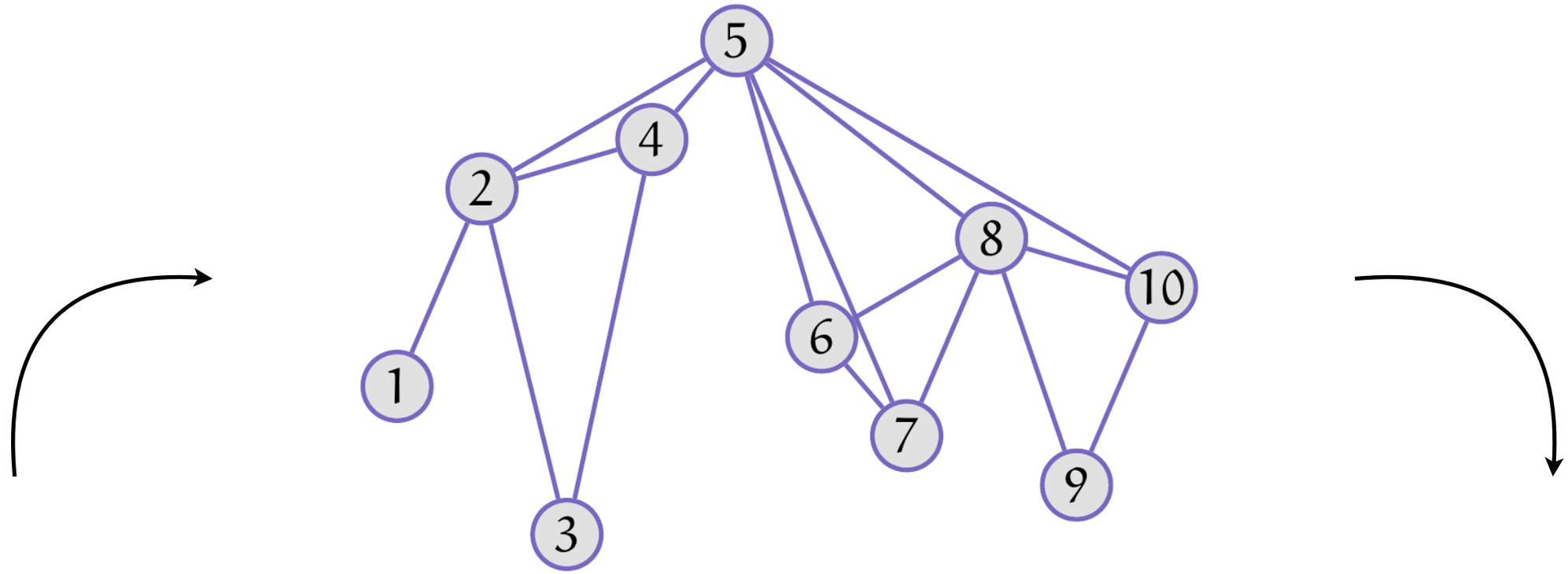


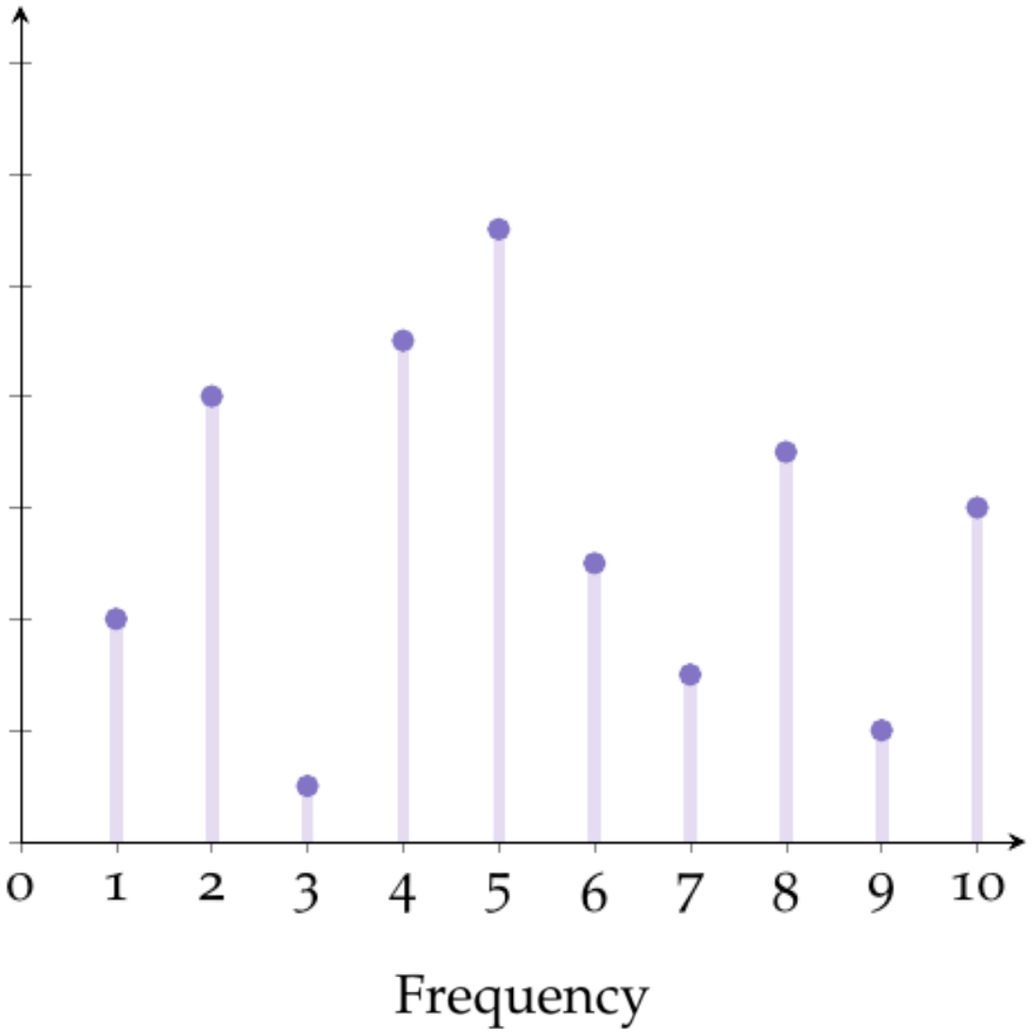
SPECTRAL VISIBILITY GRAPHS

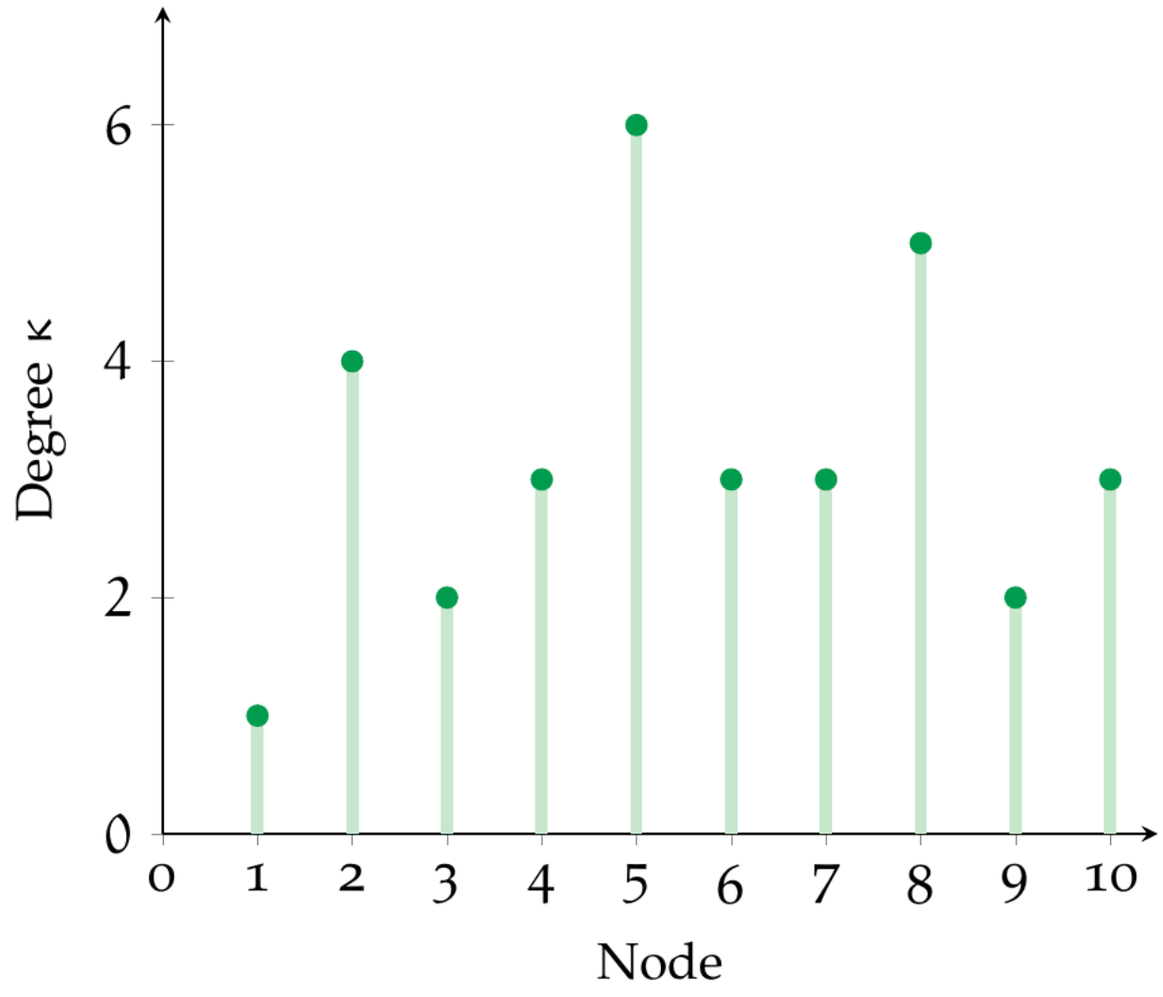


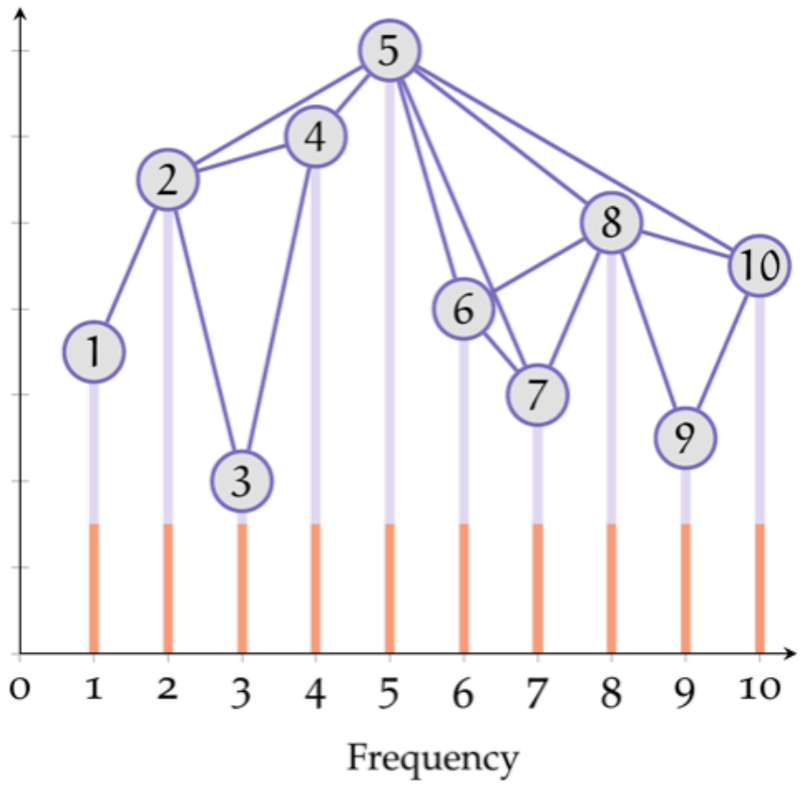



0
0.25
0.5
Time (s)
0
1000
2000
3000
4000
5000
Frequency (Hz)


5
4
2
8
10
6
1
7
9
3


0 1 2 3 4 5 6 7 8 9 10
Frequency


Degree κ
0
2
4
6
0 1 2 3 4 5 6 7 8 9 10
Node


5
4
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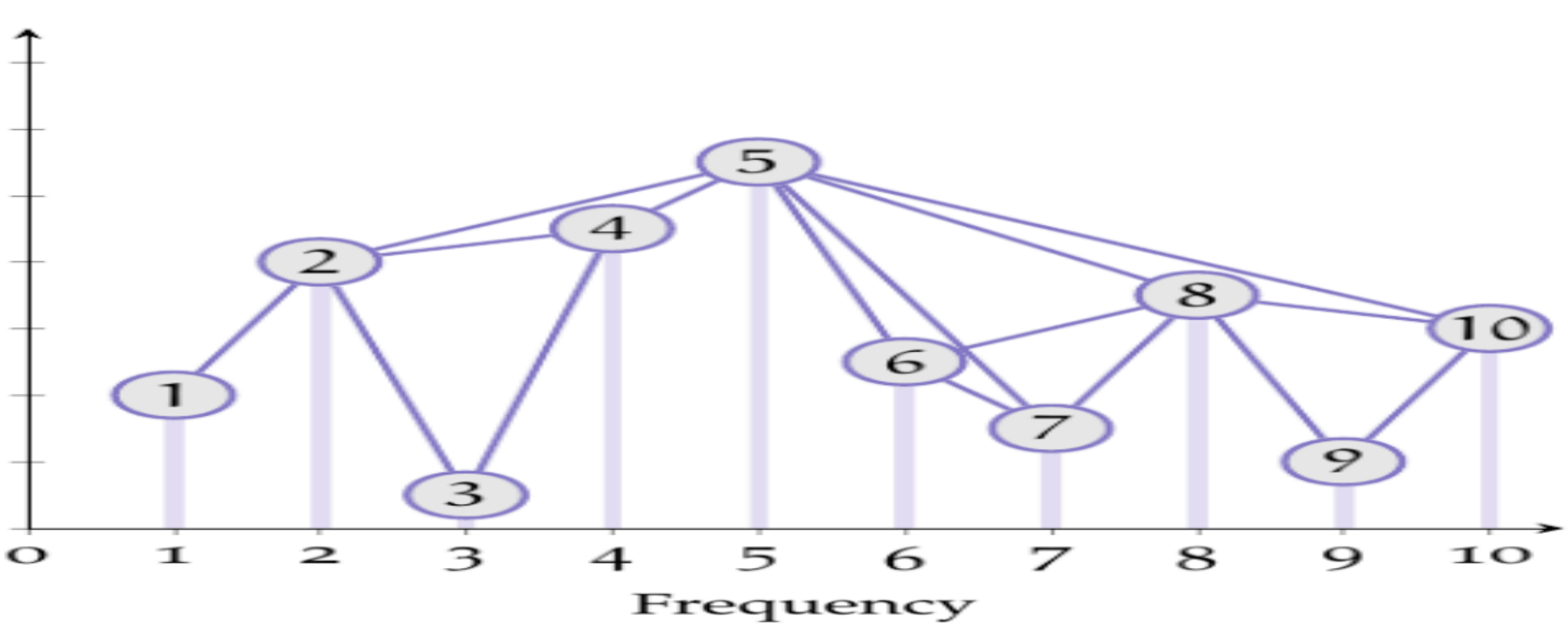
8
10
6
1
7
9
3
0 1 2 3 4 5 6 7 8 9 10
Frequency


5
4
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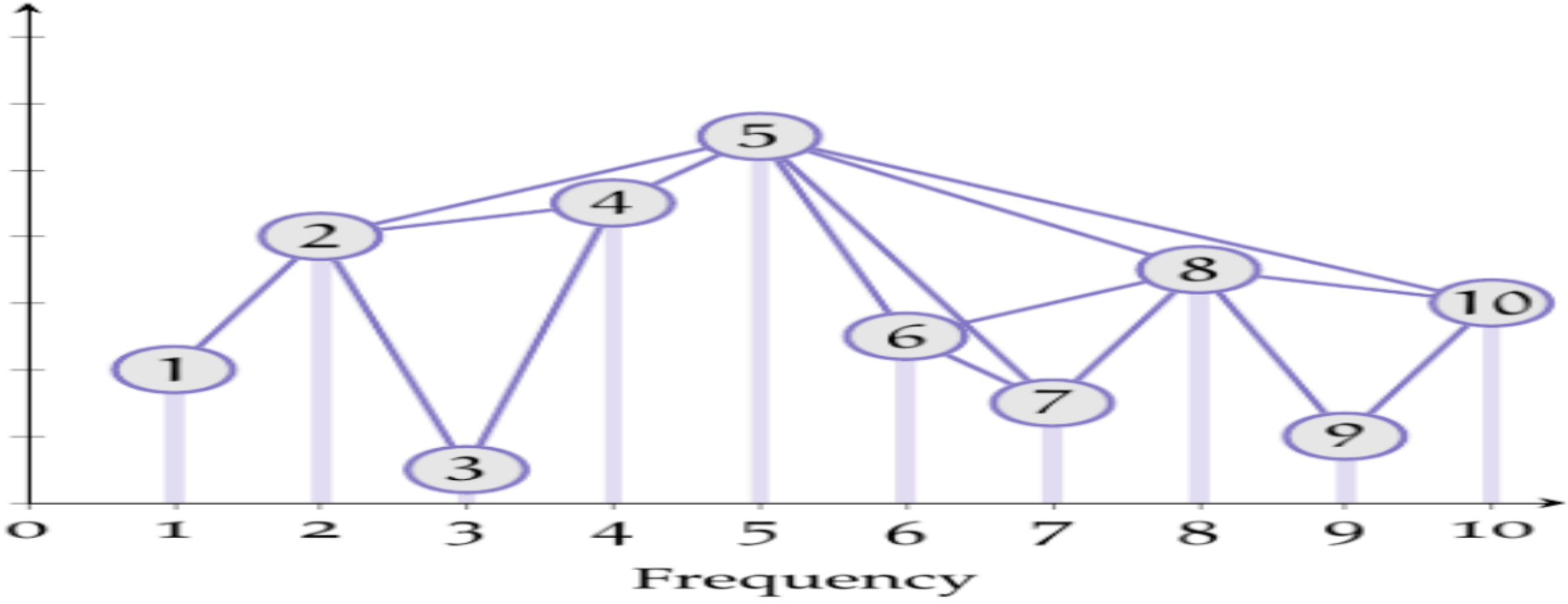
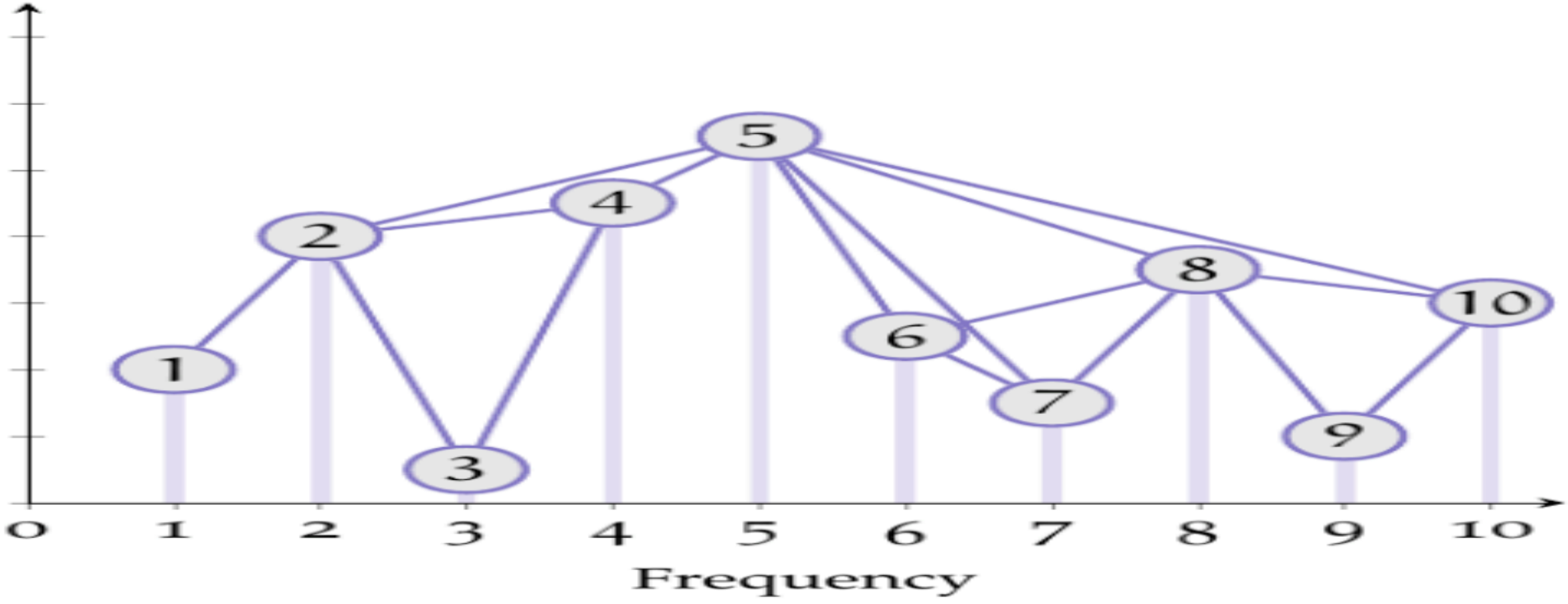
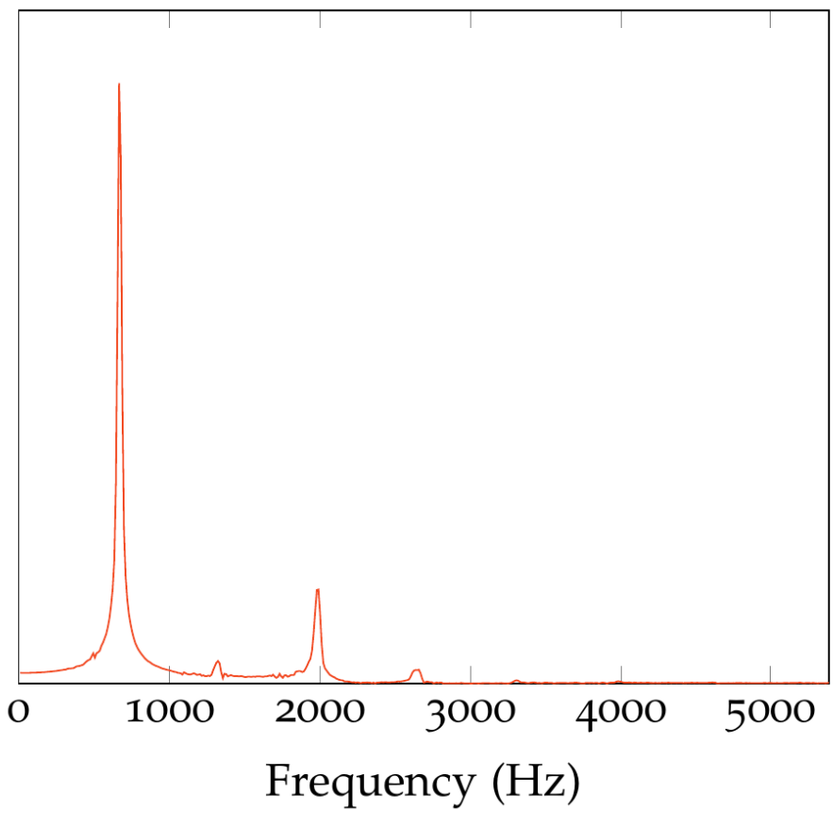
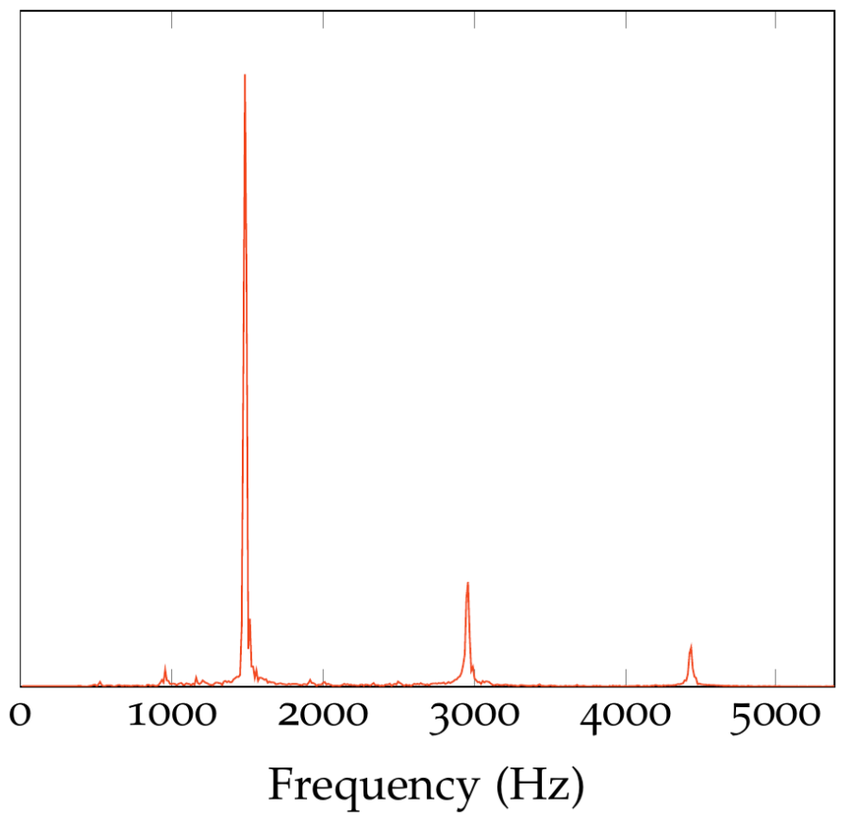
8
10
6
1
7
9
3
0 1 2 3 4 5 6 7 8 9 10
Frequency


5
4
2
8
10
6
1
7
9
3
0 1 2 3 4 5 6 7 8 9 10
Frequency


1
2
3
4
5
6
7
8
9
10
0 1 2 3 4 5 6 7 8 9 10
Frequency


0 1000 2000 3000 4000 5000
Frequency (Hz)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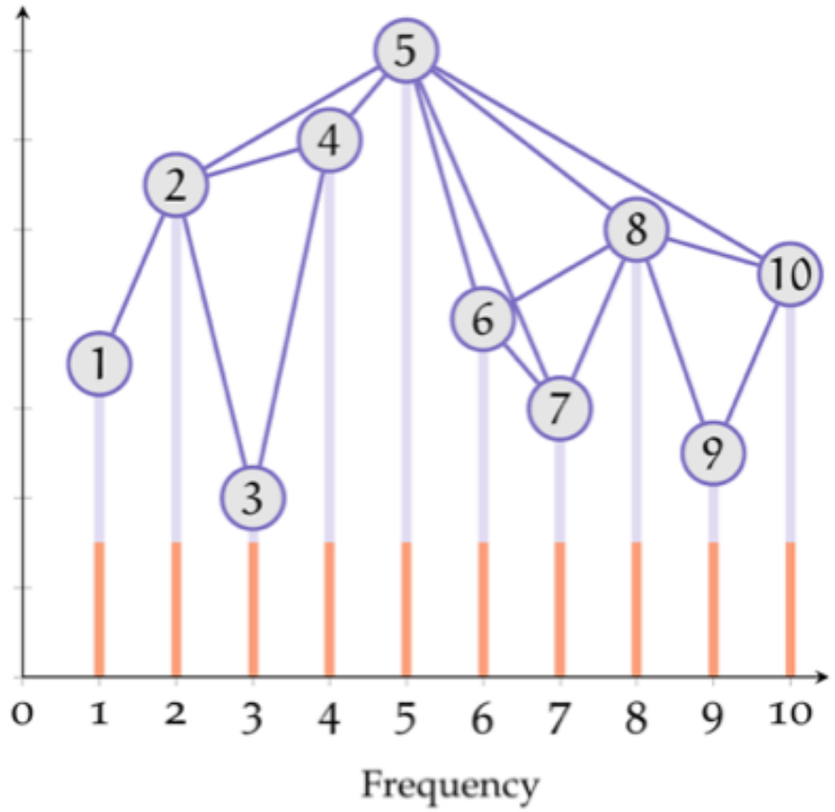
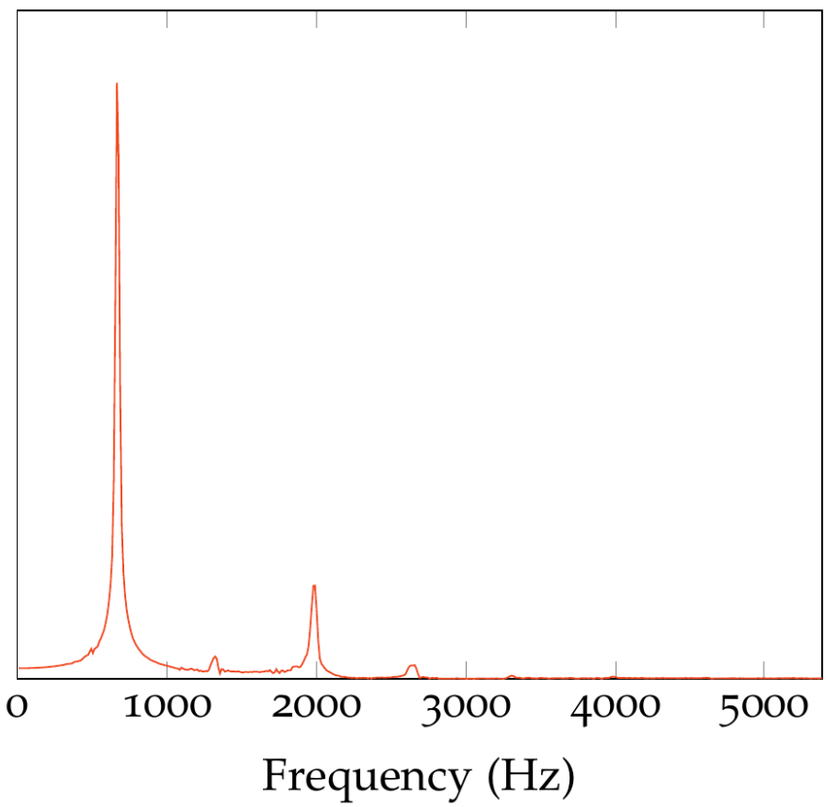
Frequency (Hz)


1
2
3
4
5
6
7
8
9
10
0 1 2 3 4 5 6 7 8 9 10
Frequency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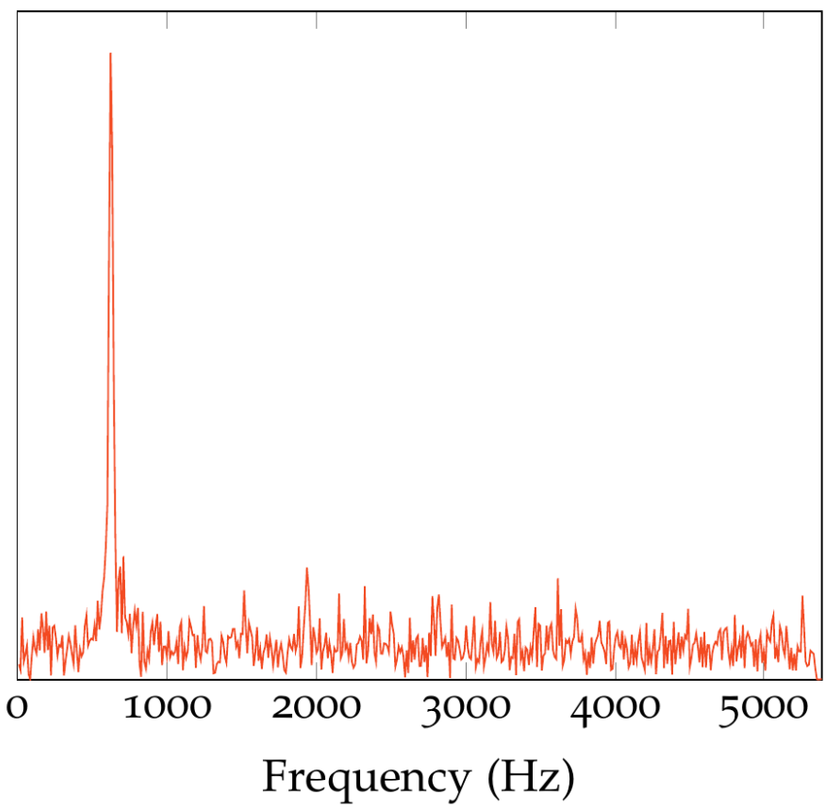
Frequency (Hz)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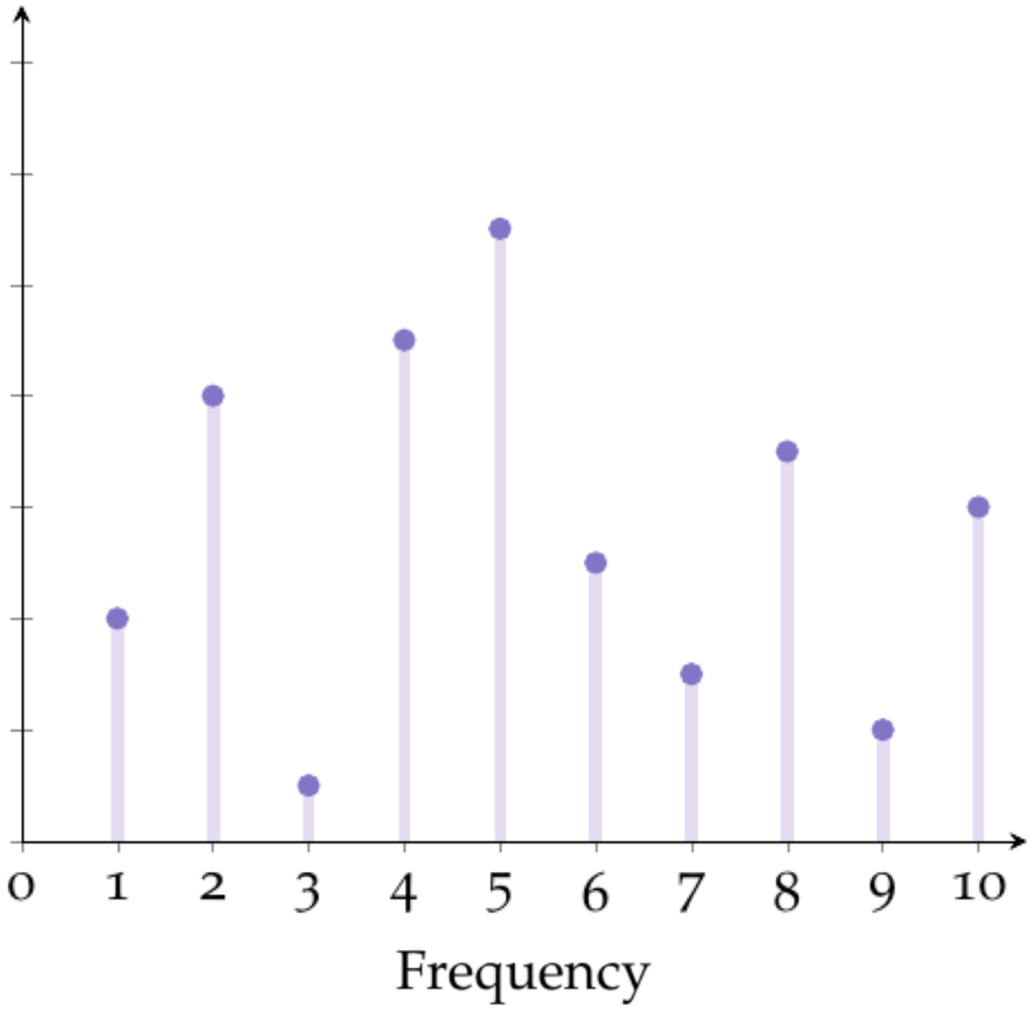
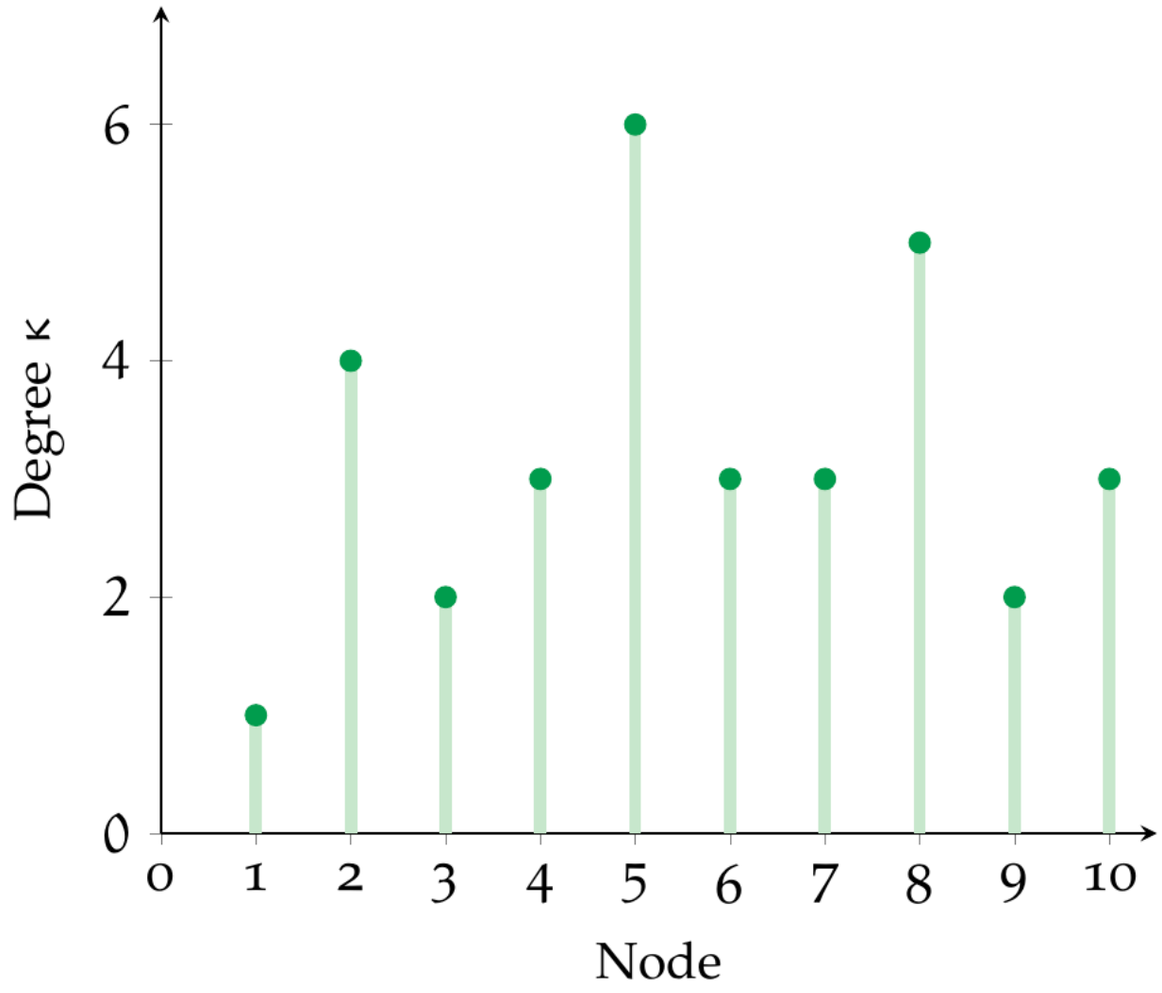
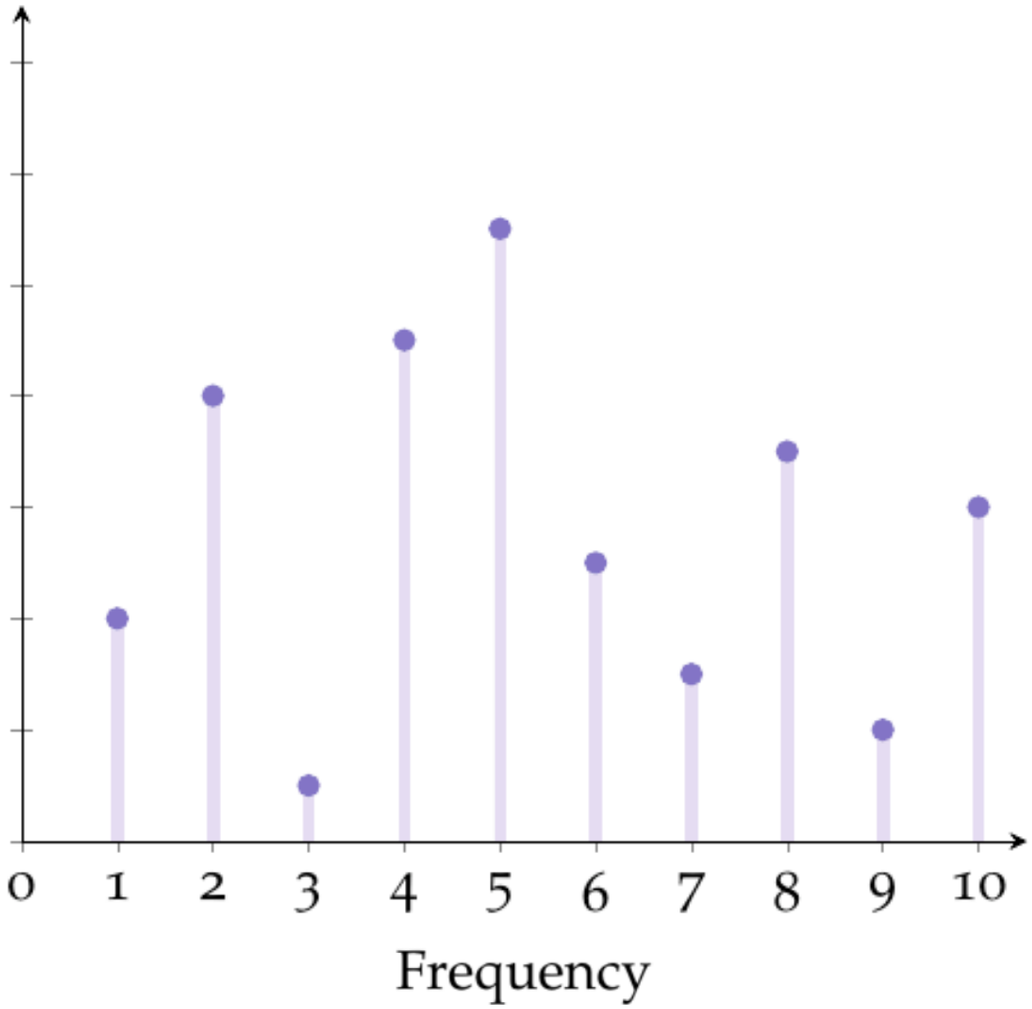
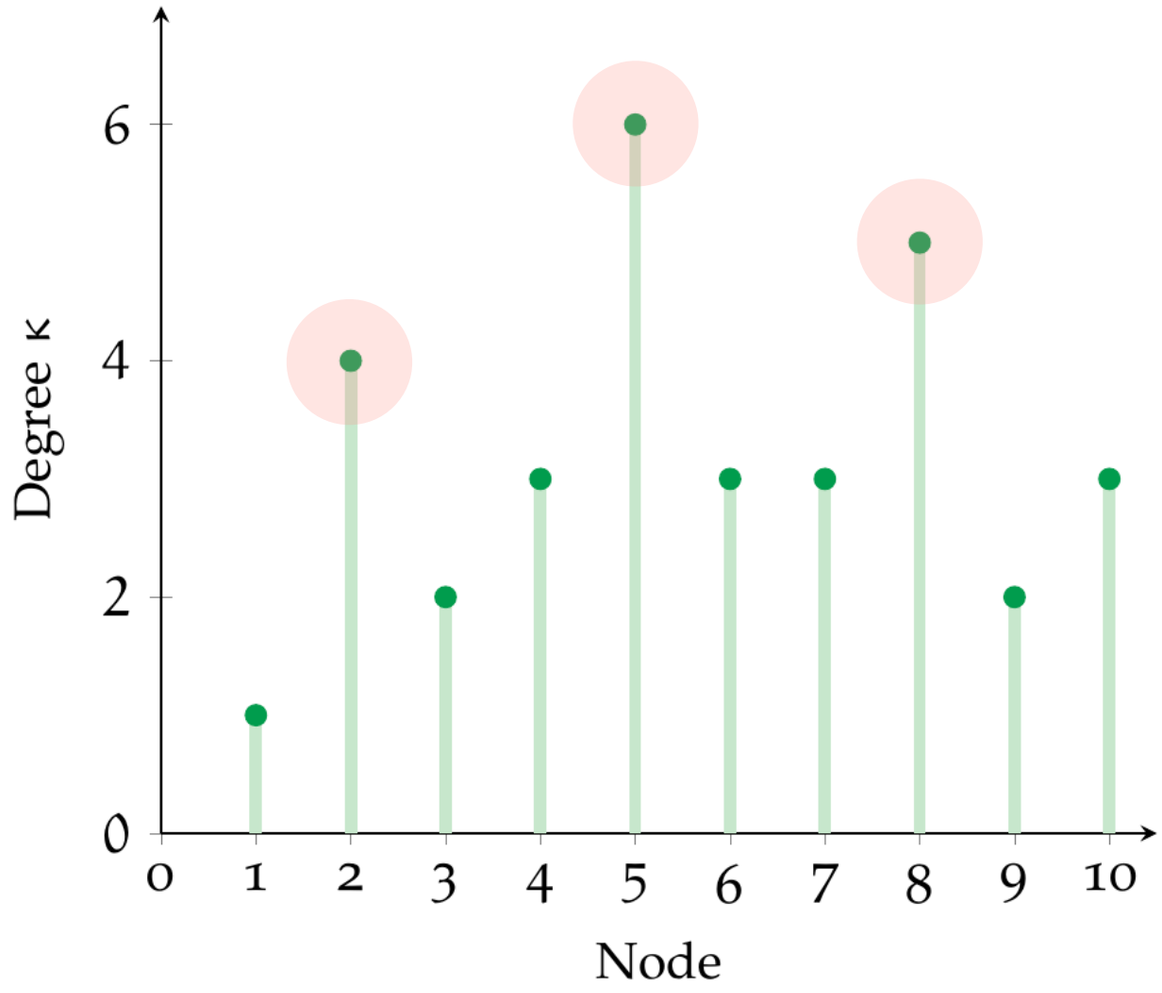
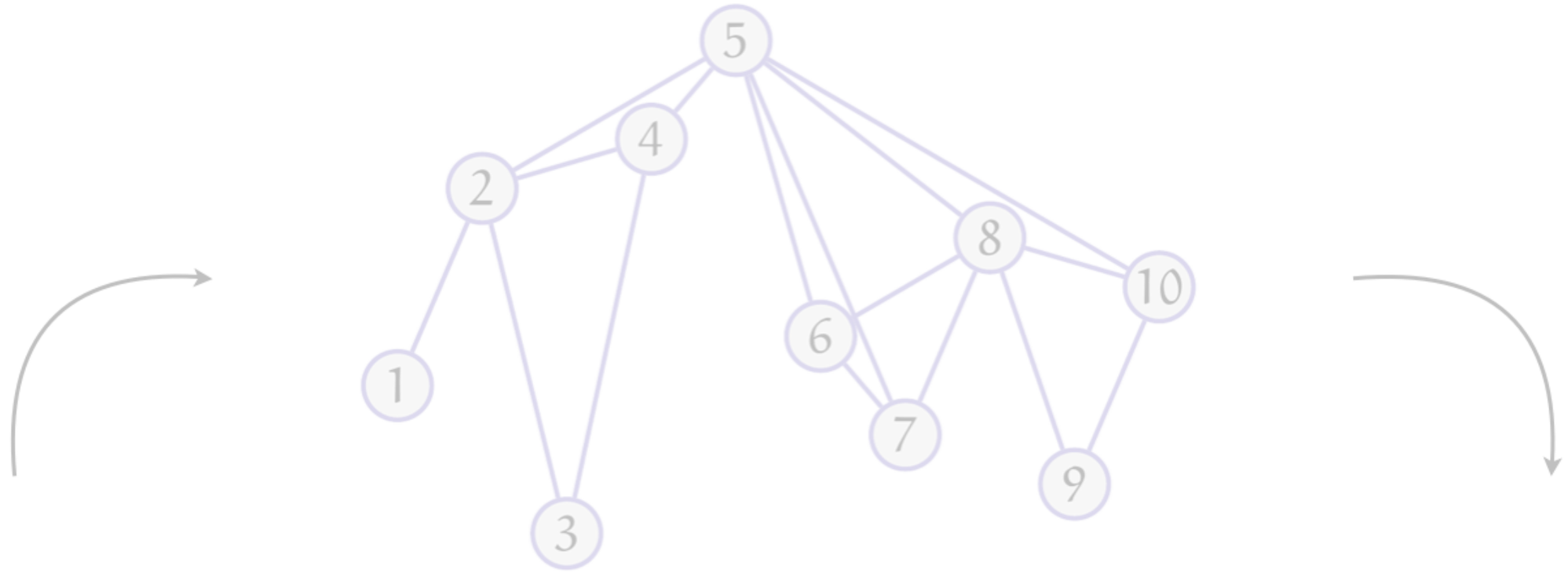
Frequency (Hz)

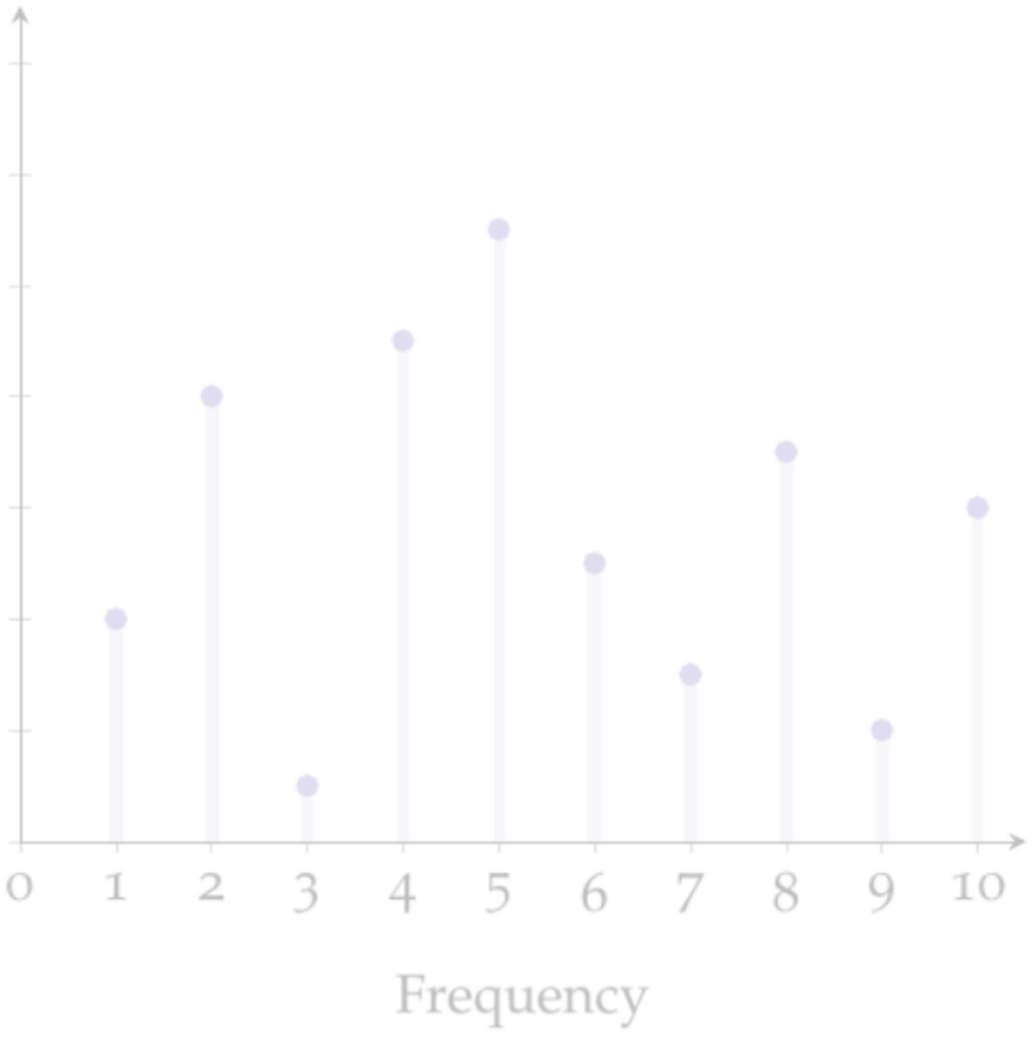

0
1
2
3
4
5
6
7
8
9
10
Frequency

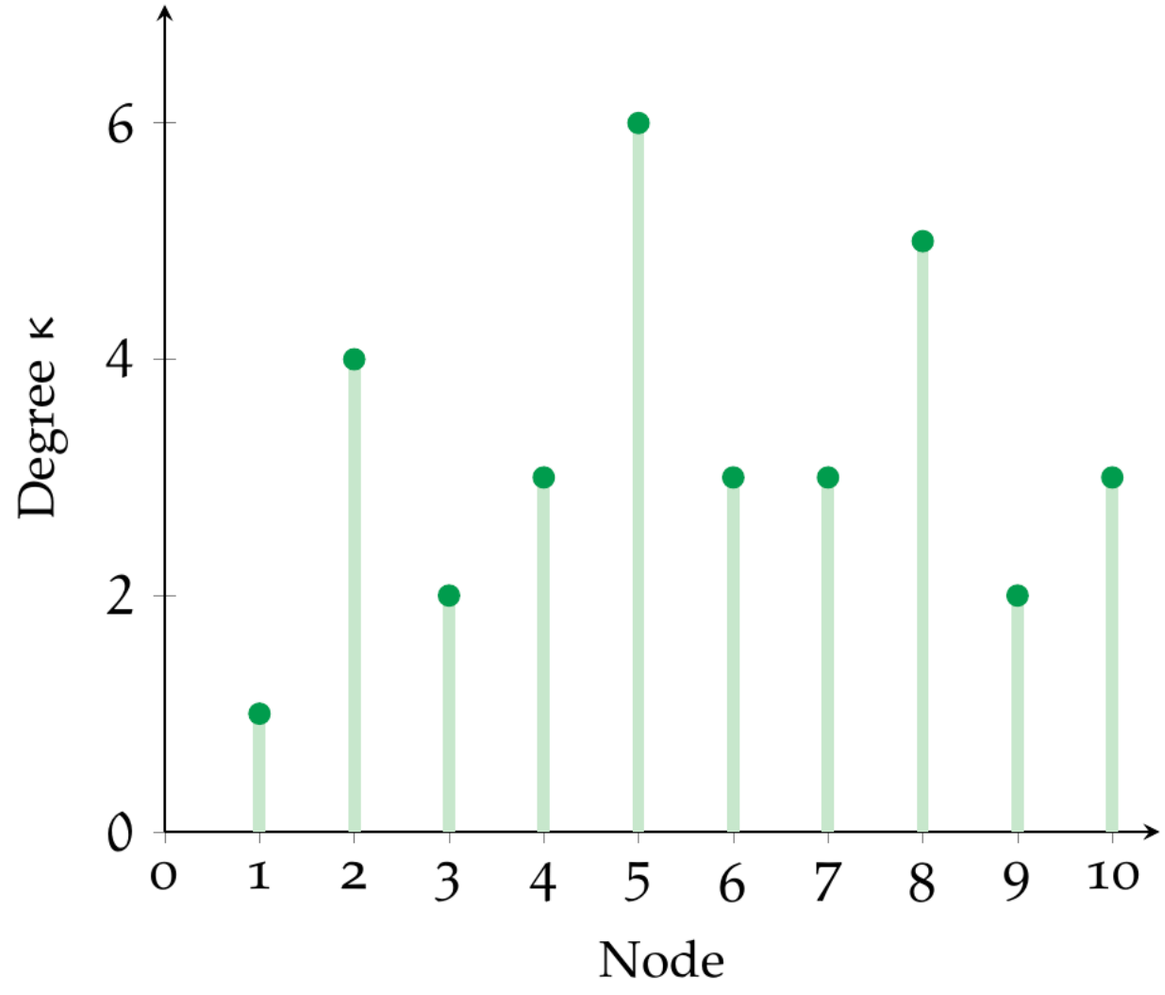

Degree κ
0
2
4
6
0
1
2
3
4
5
6
7
8
9
10
Node


0
1
2
3
4
5
6
7
8
9
10
Frequency

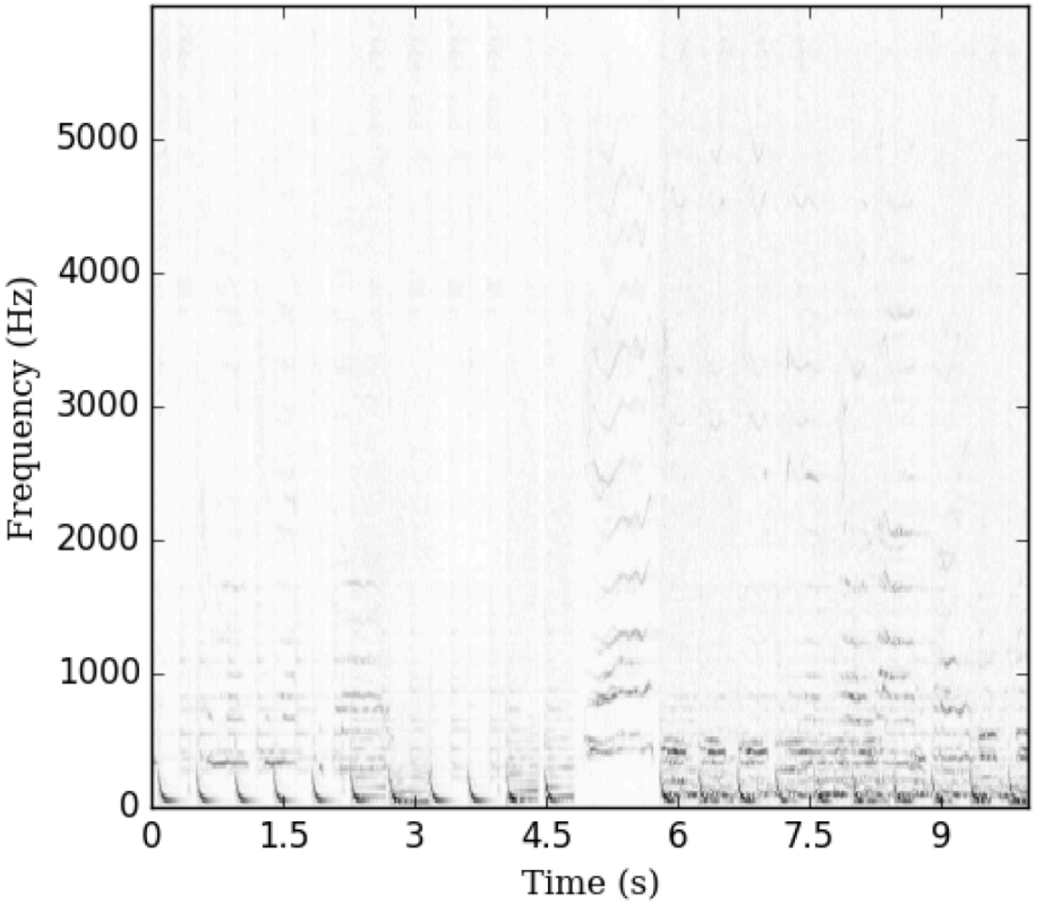

Degree κ
0
2
4
6
0
1
2
3
4
5
6
7
8
9
10
Node


5
4
2
8
10
6
1
7
9
3

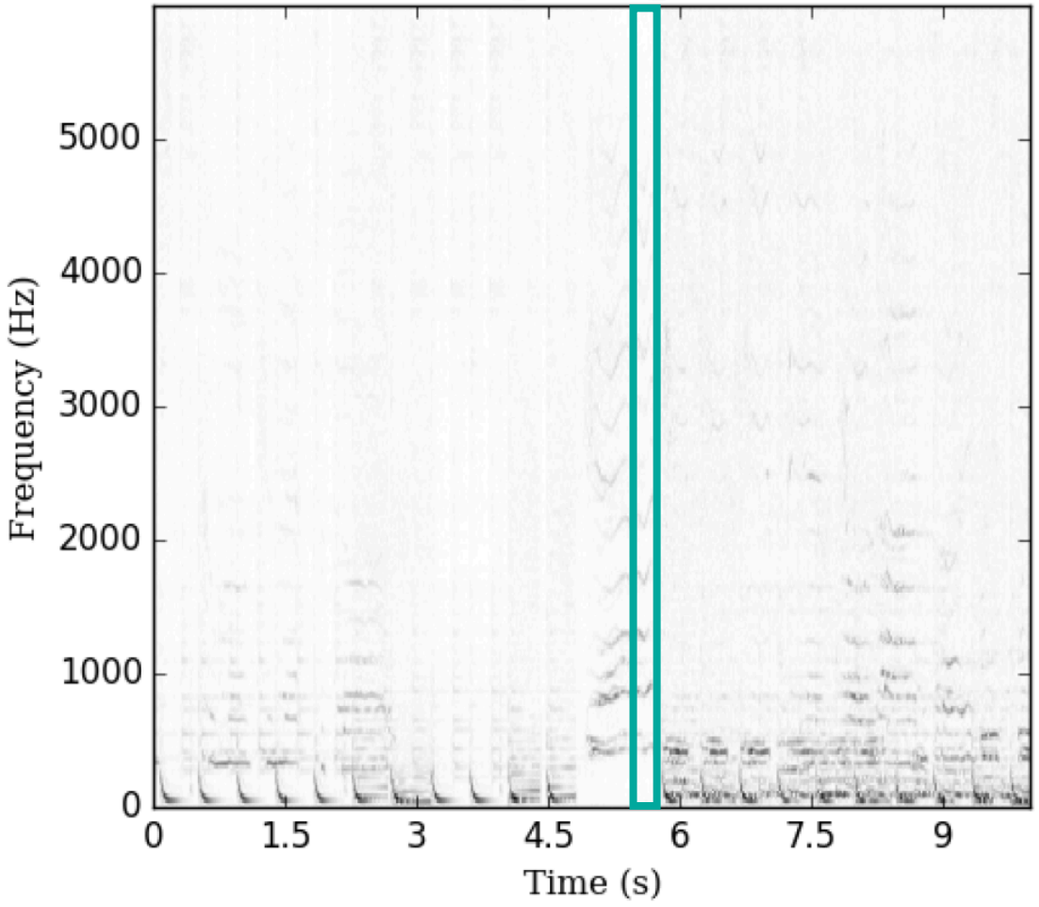

0 1 2 3 4 5 6 7 8 9 10
Frequency

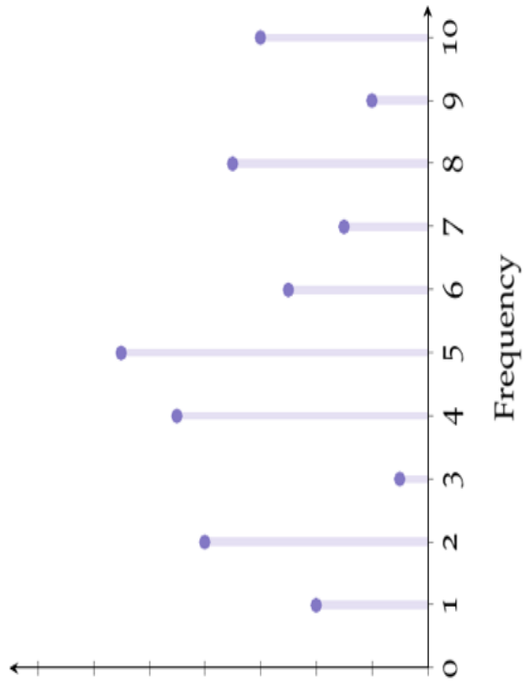

Degree κ
0
2
4
6
0 1 2 3 4 5 6 7 8 9 10
Node

A. Spectrogram

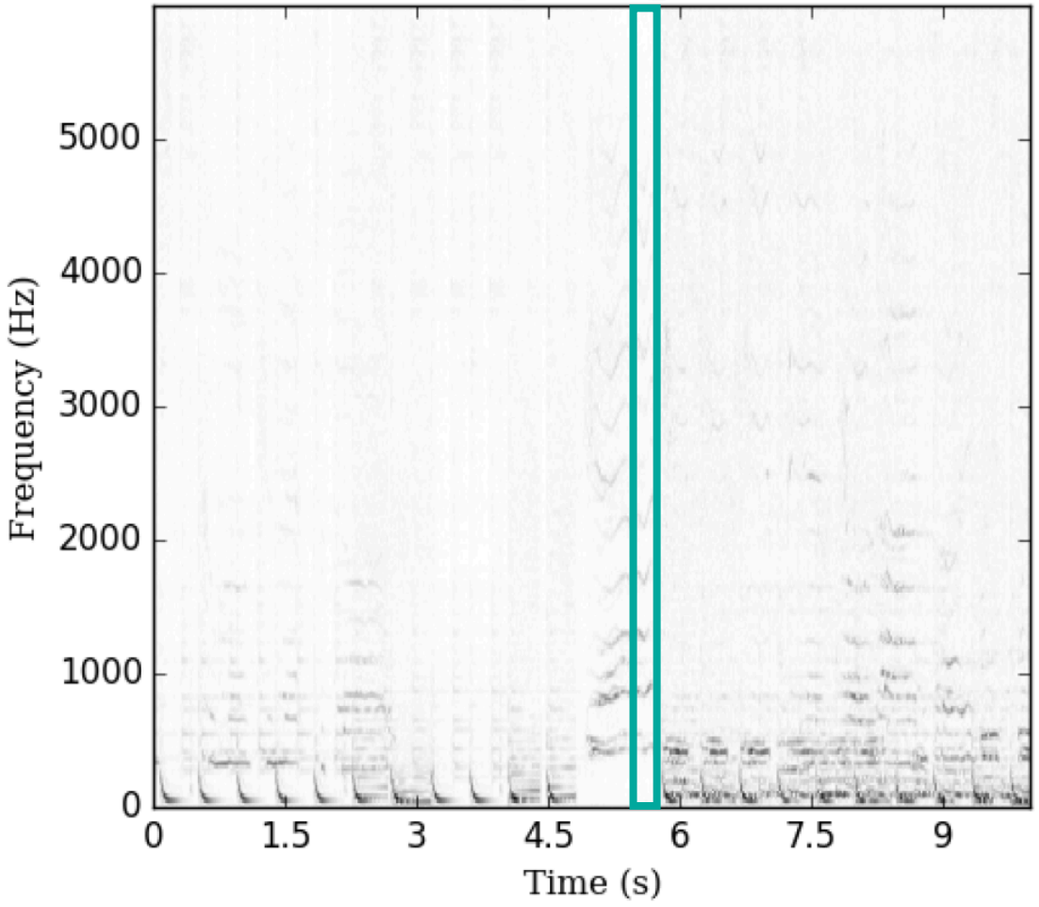


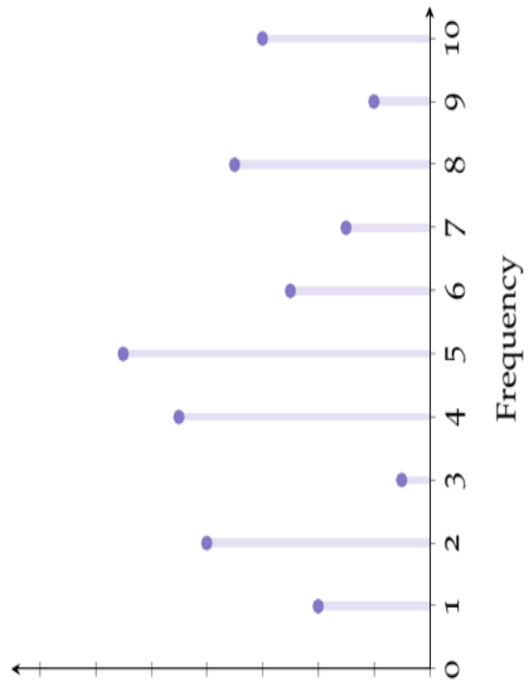
A. Spectrogram

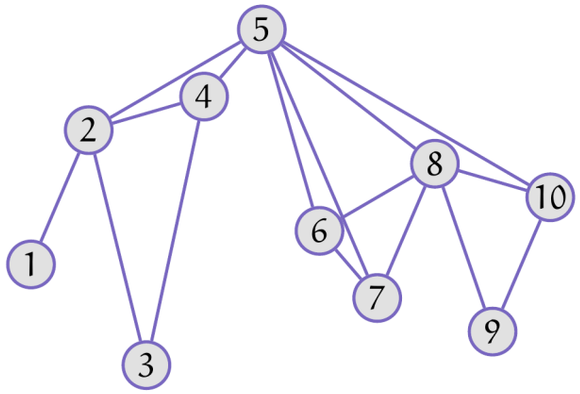




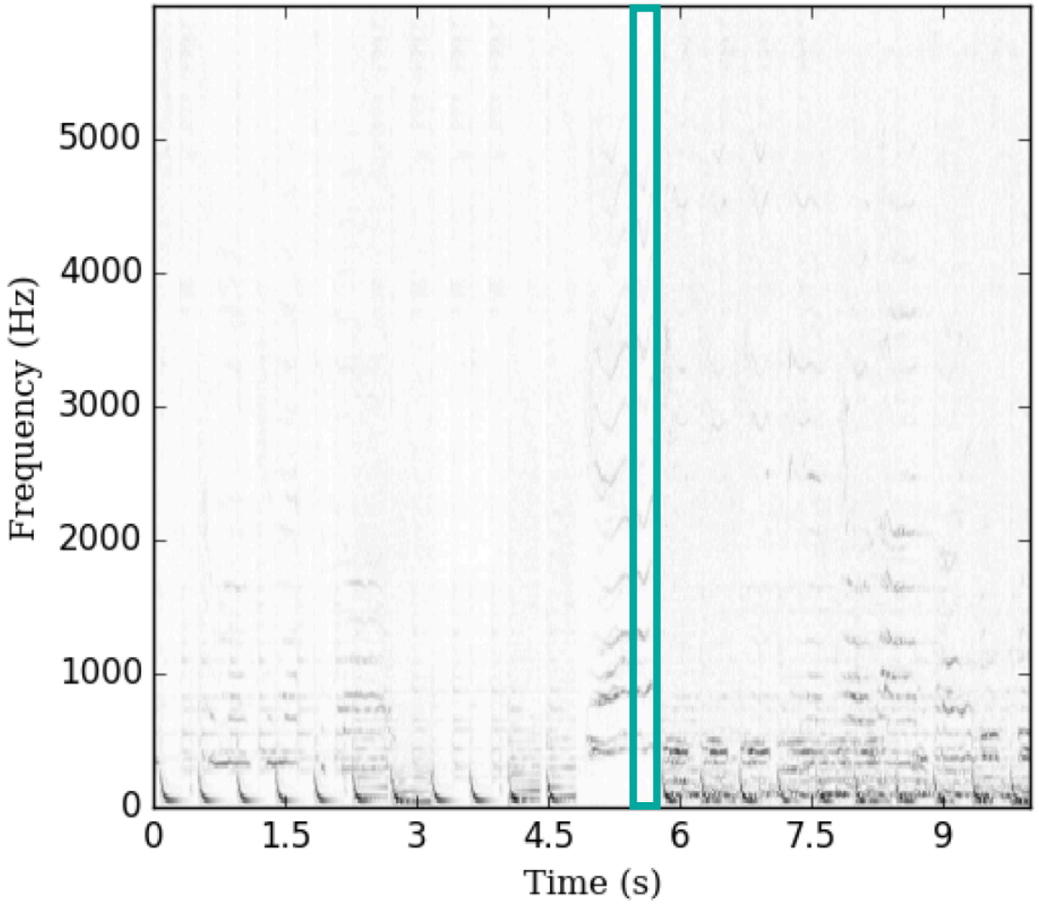
A. Spectrogram

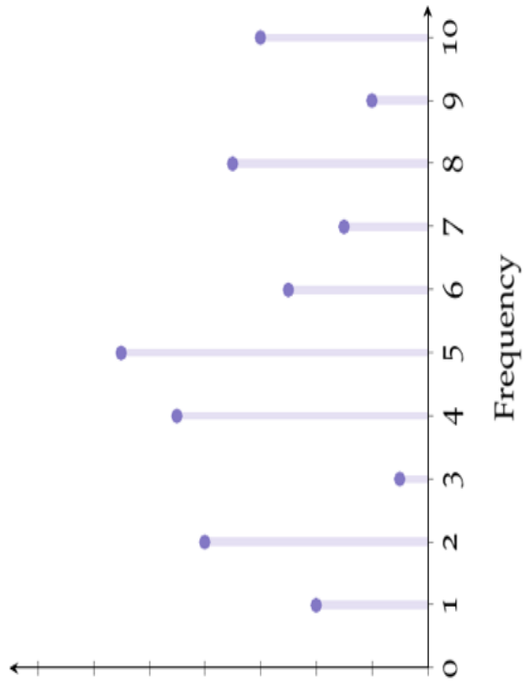


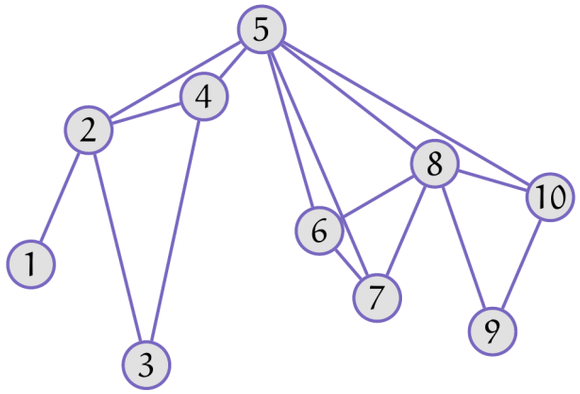


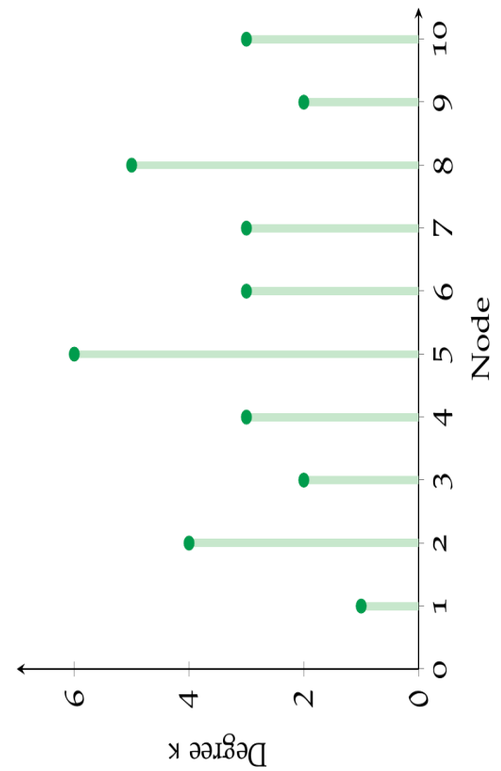


A. Spectrogram

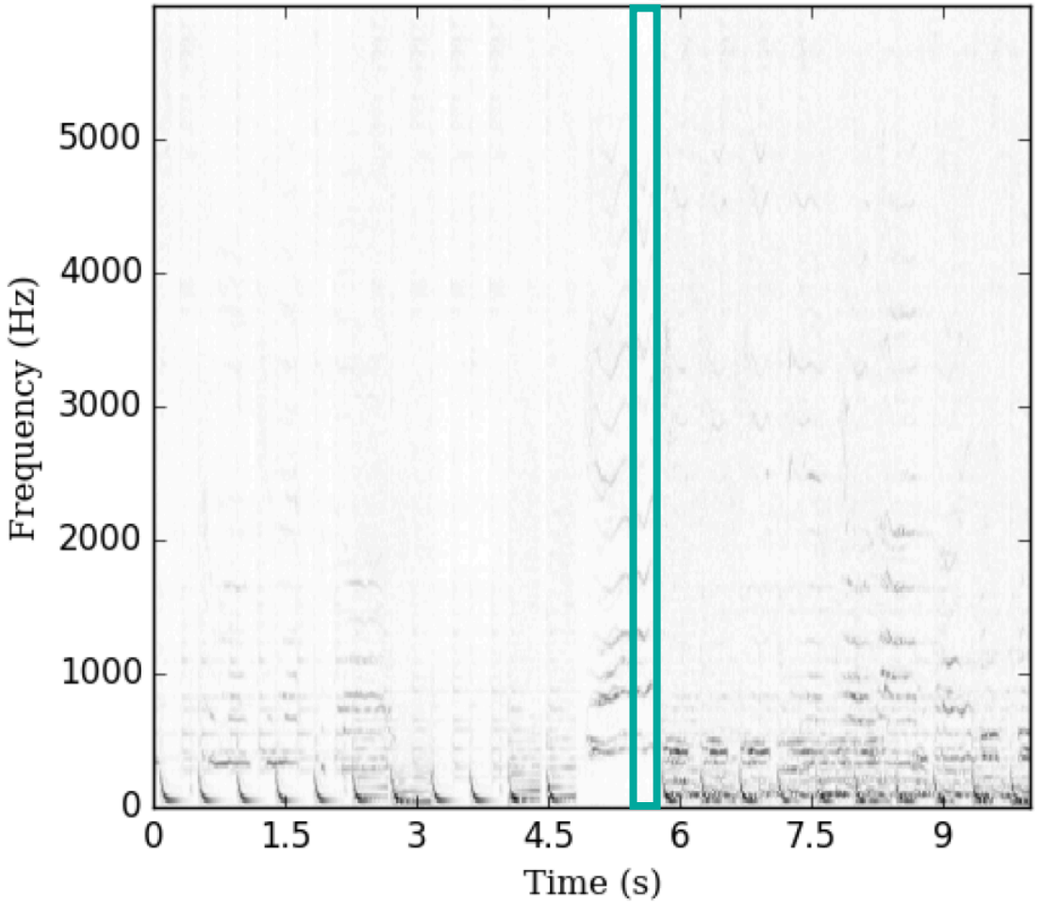


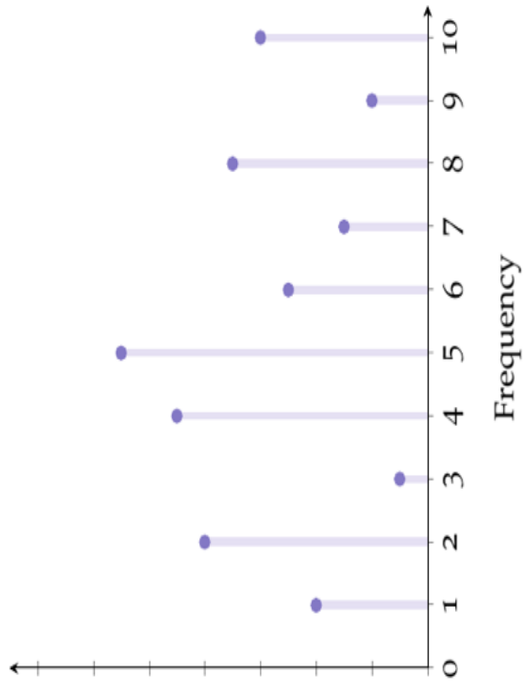


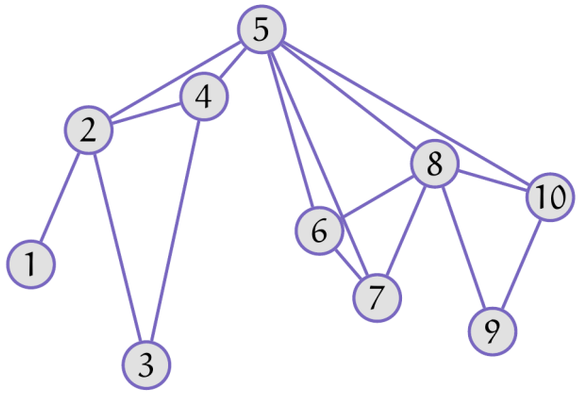


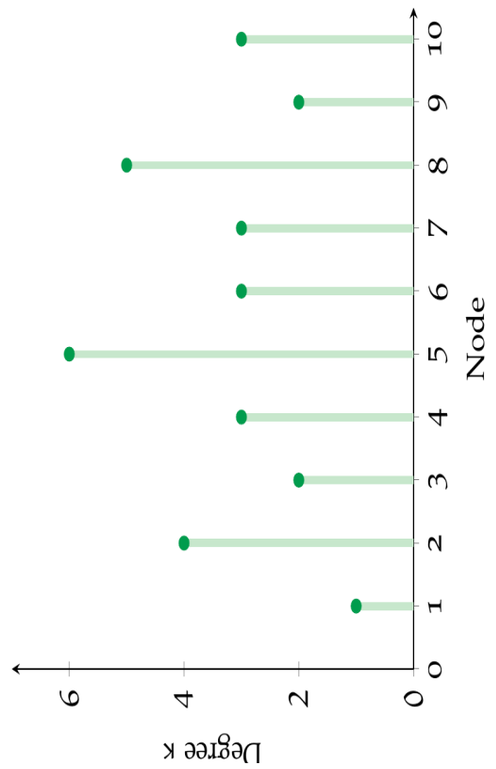


A. Spectrogram

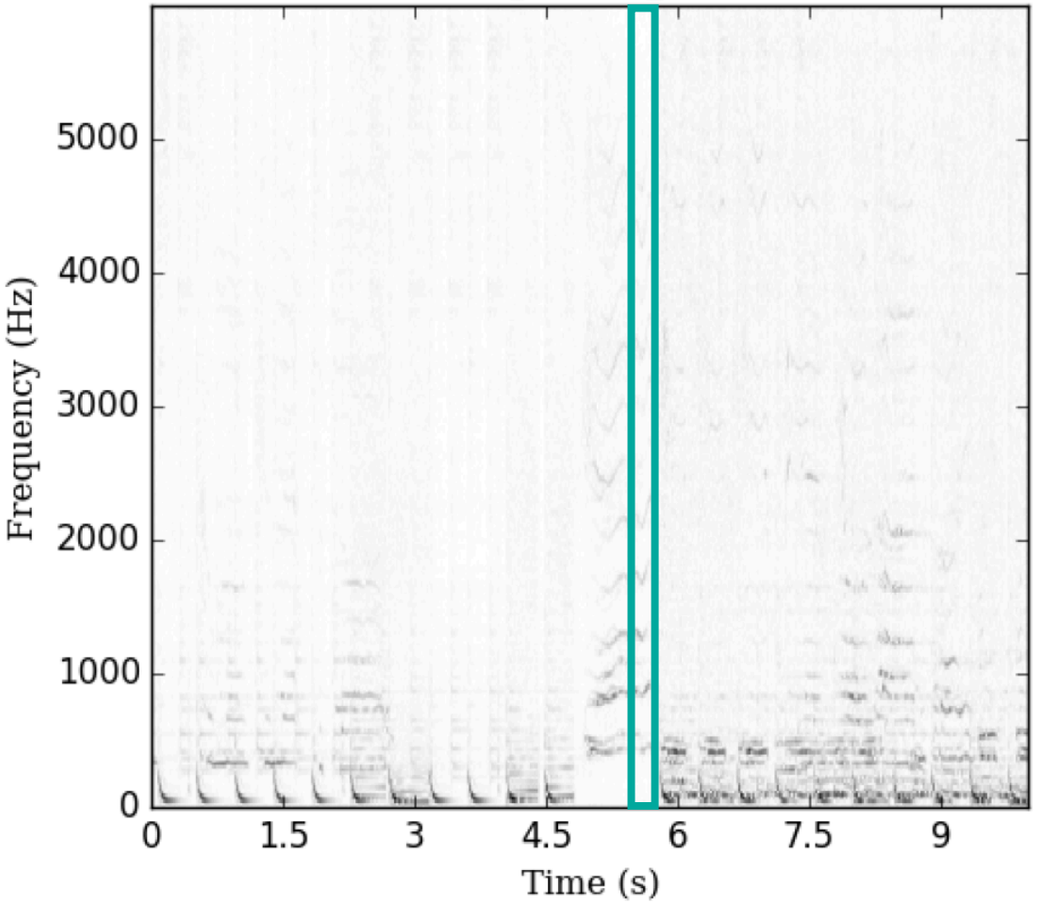


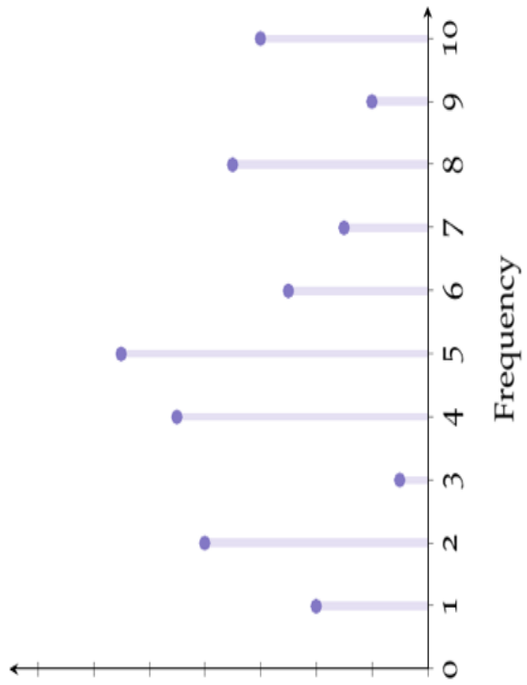


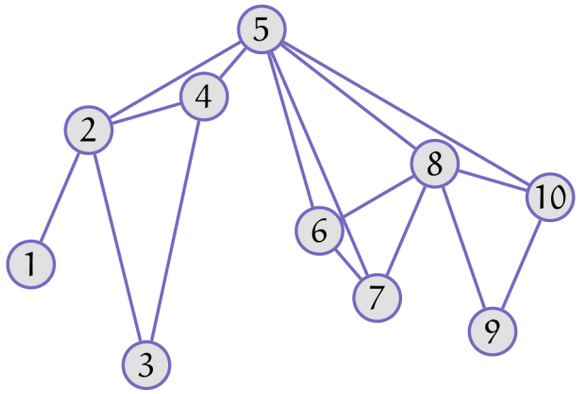


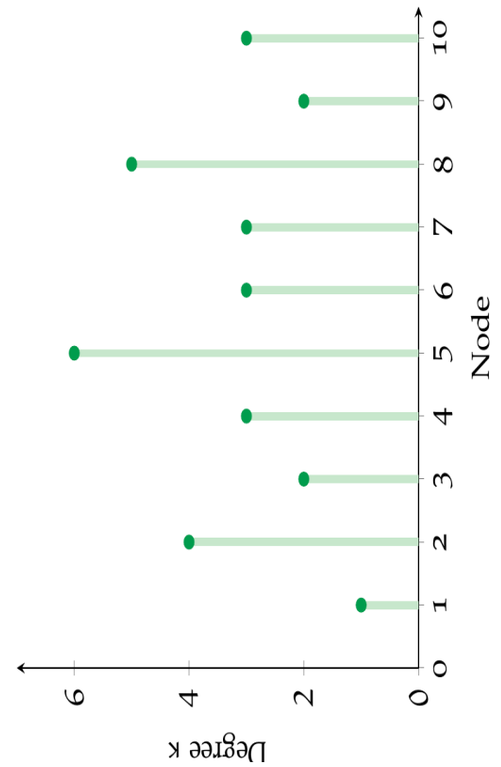


A. Spectrogram



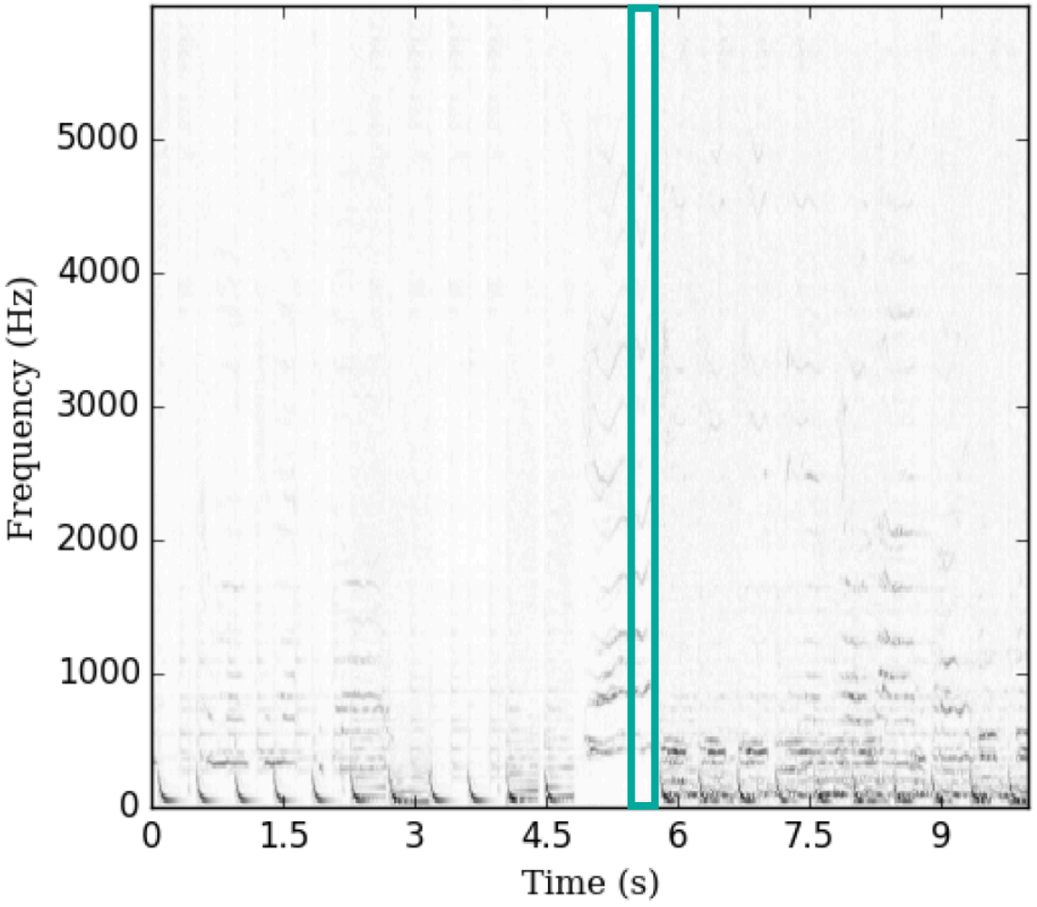


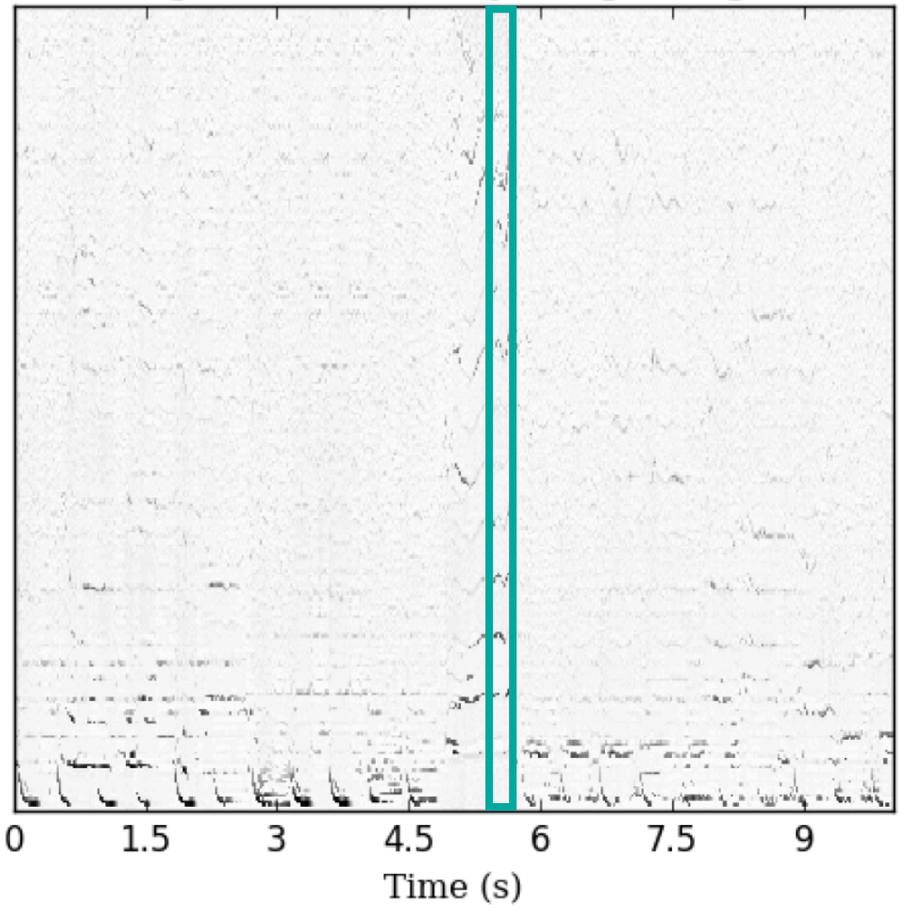


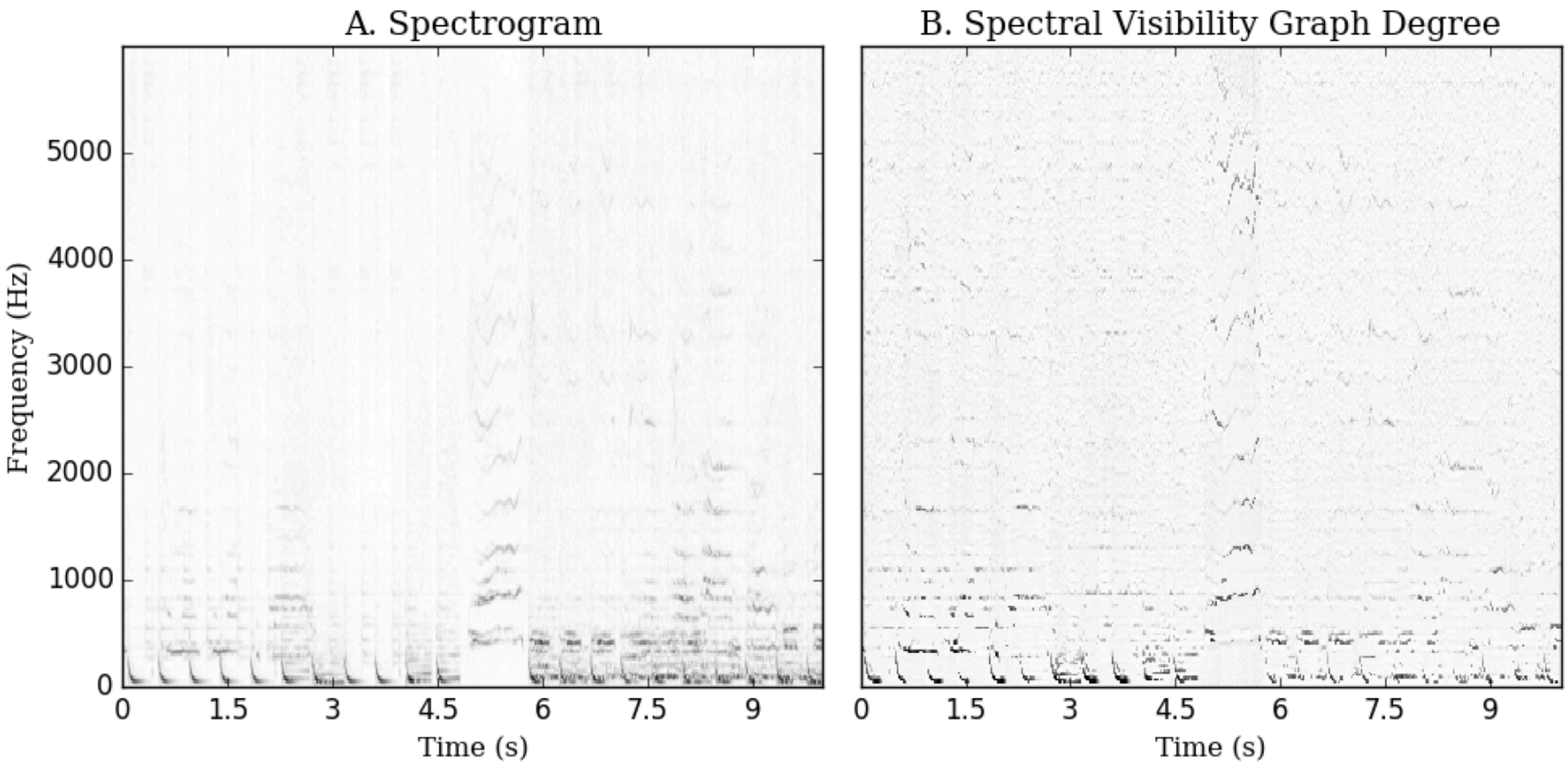


A. Spectrogram

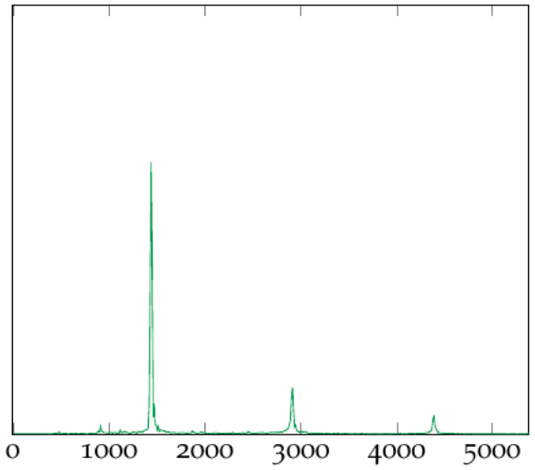
B. Spectral Visibility Graph Degree

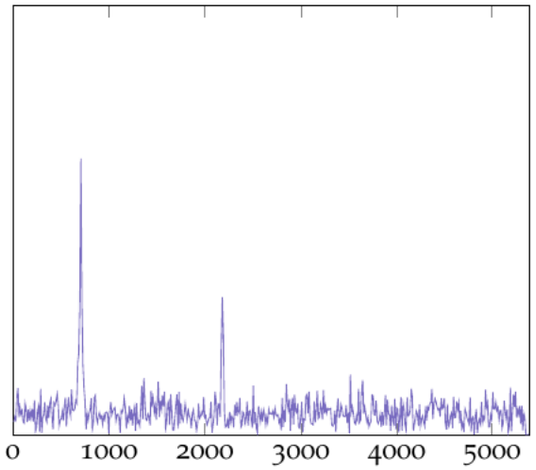


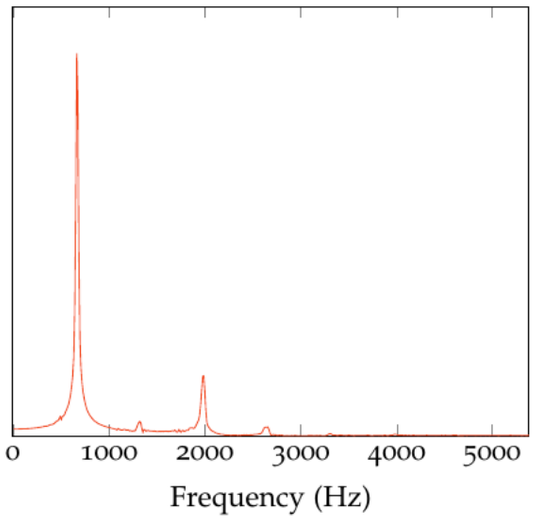


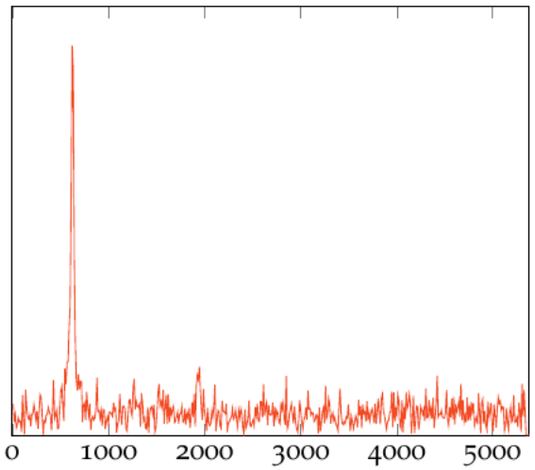

A. Spectrogram
B. Spectral Visibility Graph Degree
Frequency (Hz)
5000
4000
3000
2000
1000
0
0
1.5
3
4.5
6
7.5
9
Time (s)
Time (s)

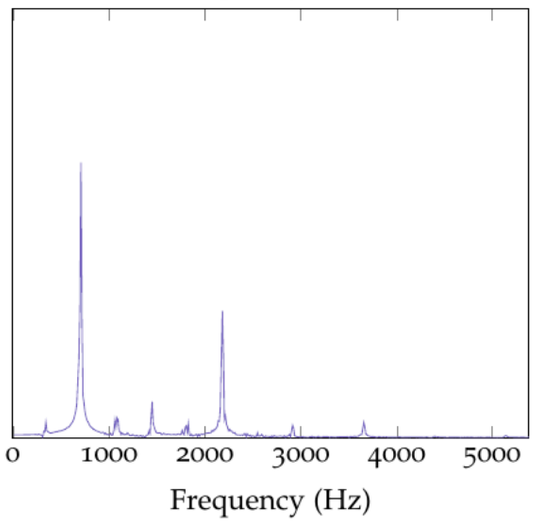
EXPERIMENTS

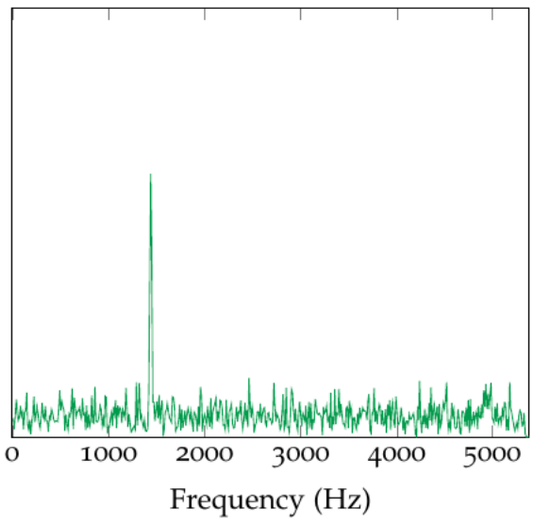

0
1000
2000
3000
4000
5000
Frequency (Hz)

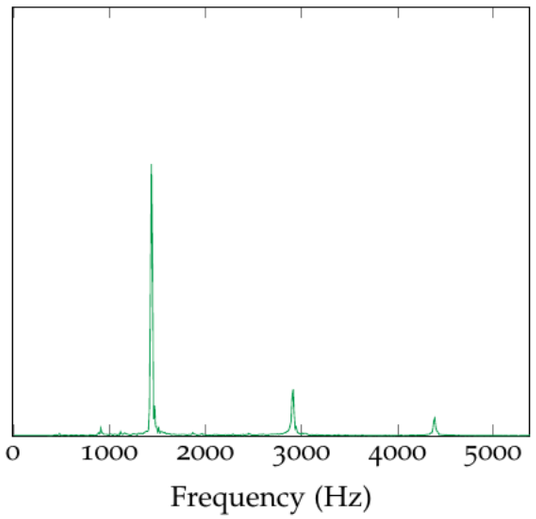

0
1000
2000
3000
4000
5000
Frequency (Hz)

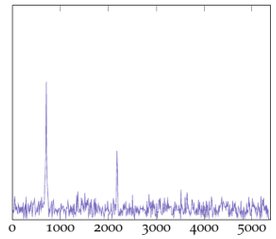

0
1000
2000
3000
4000
5000
Frequency (Hz)

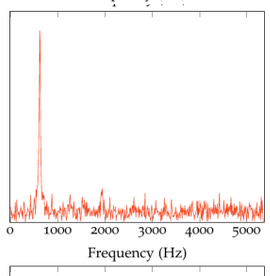

0
1000
2000
3000
4000
5000
Frequency (Hz)

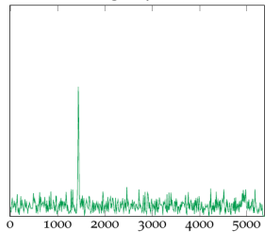

0
1000
2000
3000
4000
5000
Frequency (Hz)

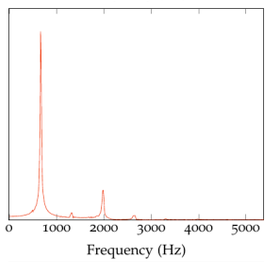

0
1000
2000
3000
4000
5000
Frequency (Hz)

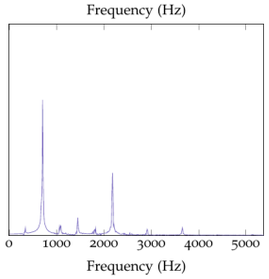

0
1000
2000
3000
4000
5000
Frequency (Hz)

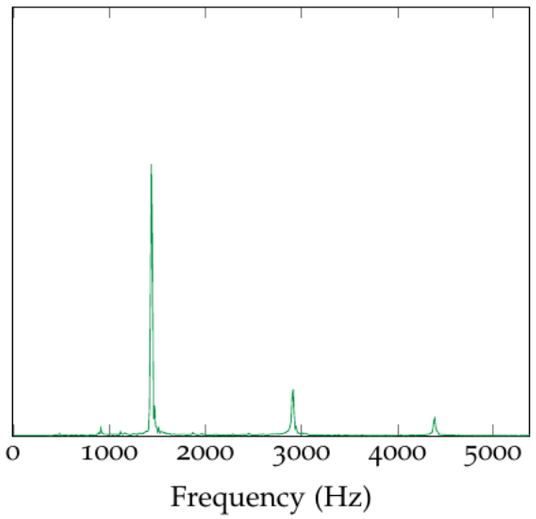

0
1000
2000
3000
4000
5000
Frequency (Hz)

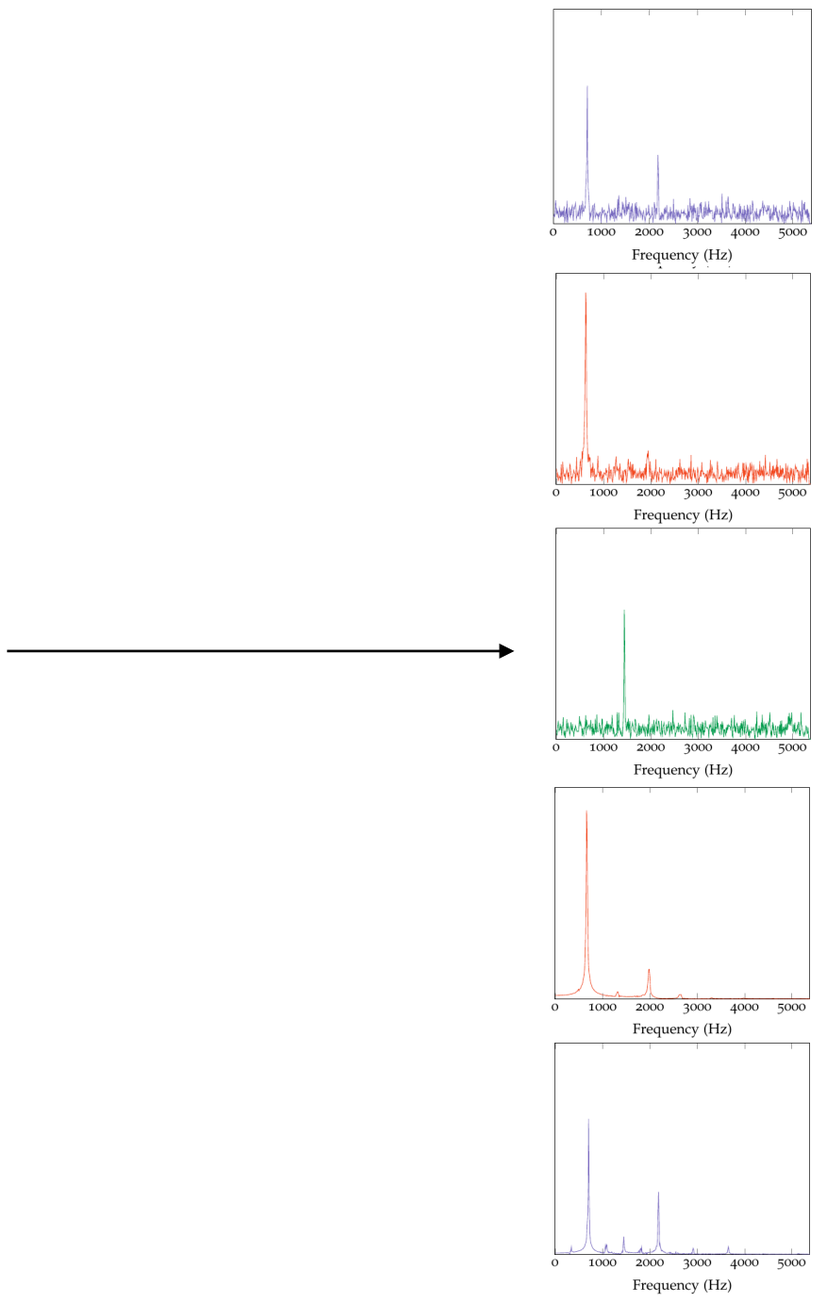

0
1000
2000
3000
4000
5000
Frequency (Hz)


0
1000
2000
3000
4000
5000
Frequency (Hz)


0
1000
2000
3000
4000
5000
Frequency (Hz)


0
1000
2000
3000
4000
5000
Frequency (Hz)


0
1000
2000
3000
4000
5000
Frequency (Hz)



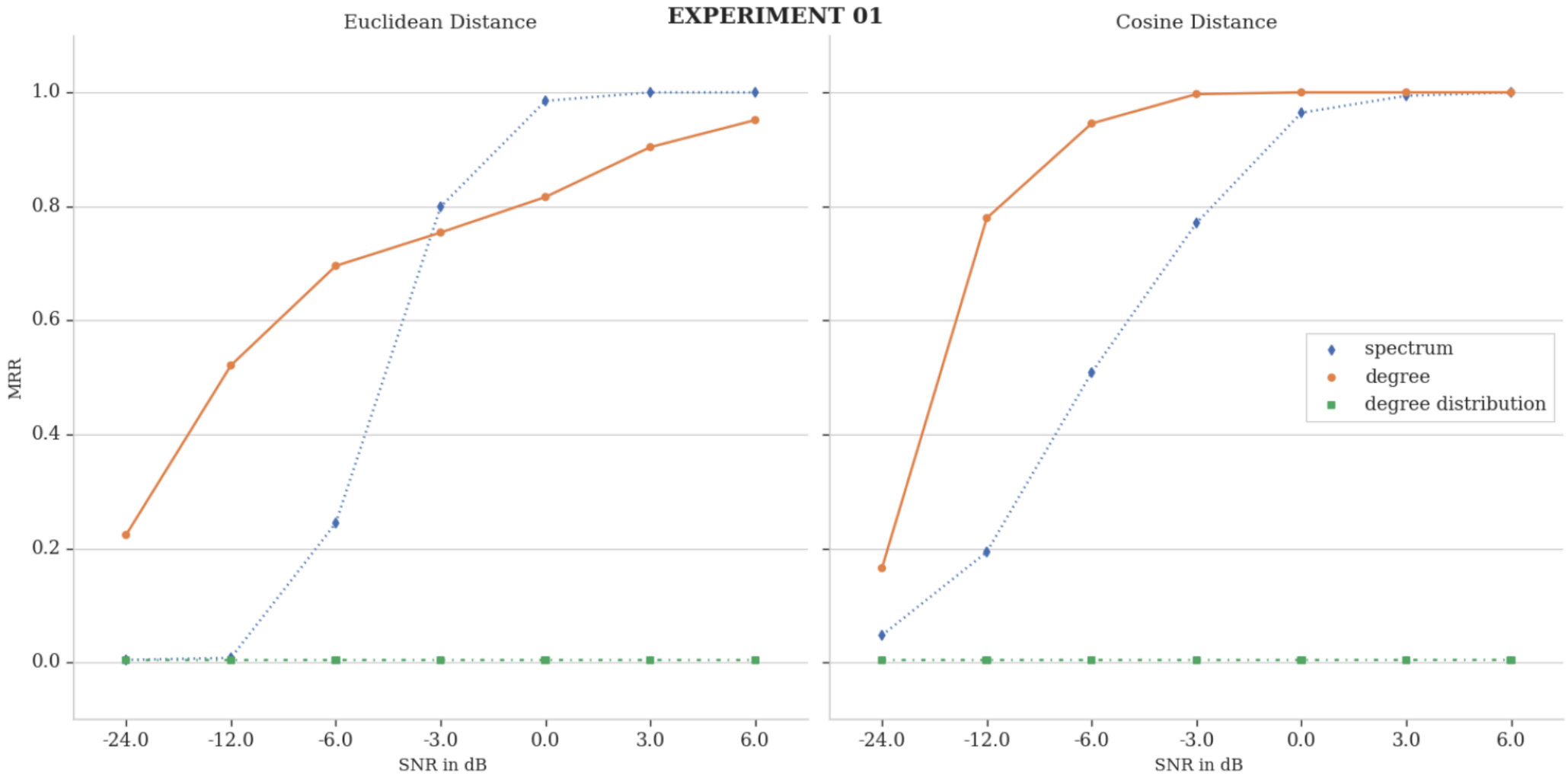
0
1000
2000
3000
4000
5000
Frequency (Hz)

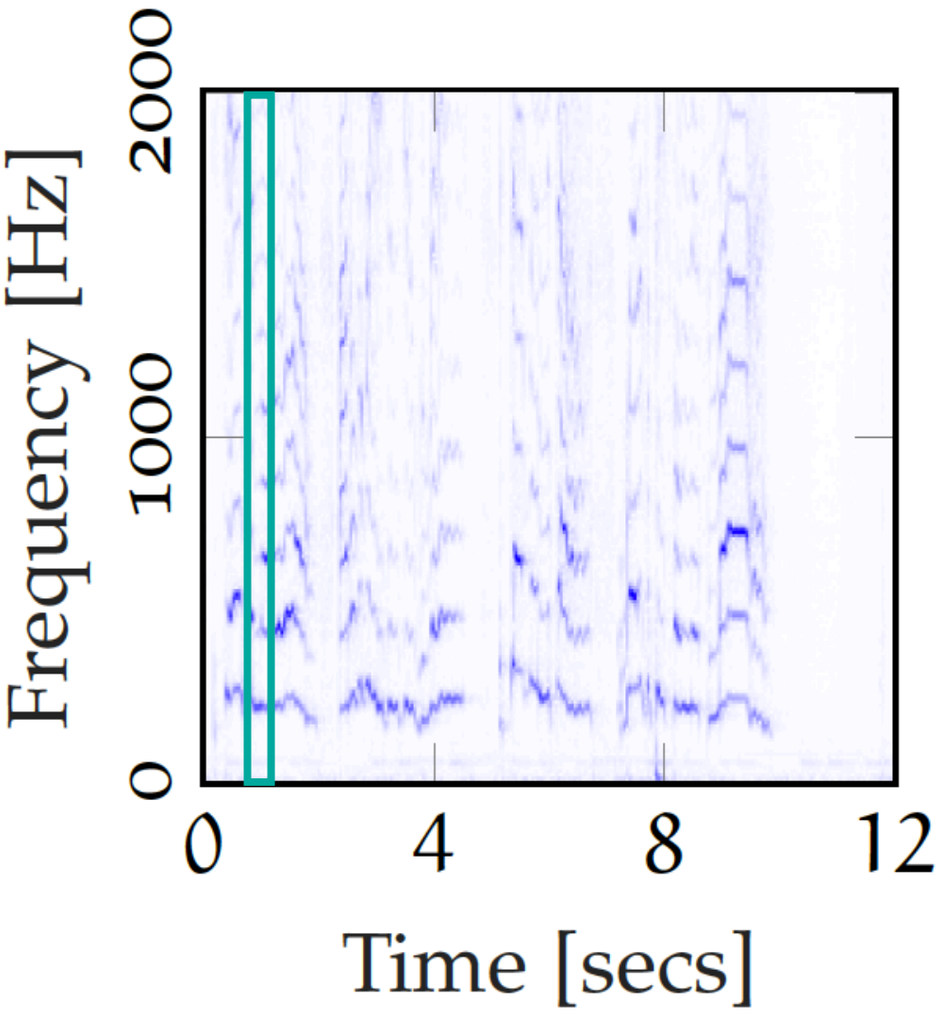
0
1000
2000
3000
4000
5000
Frequency (Hz)

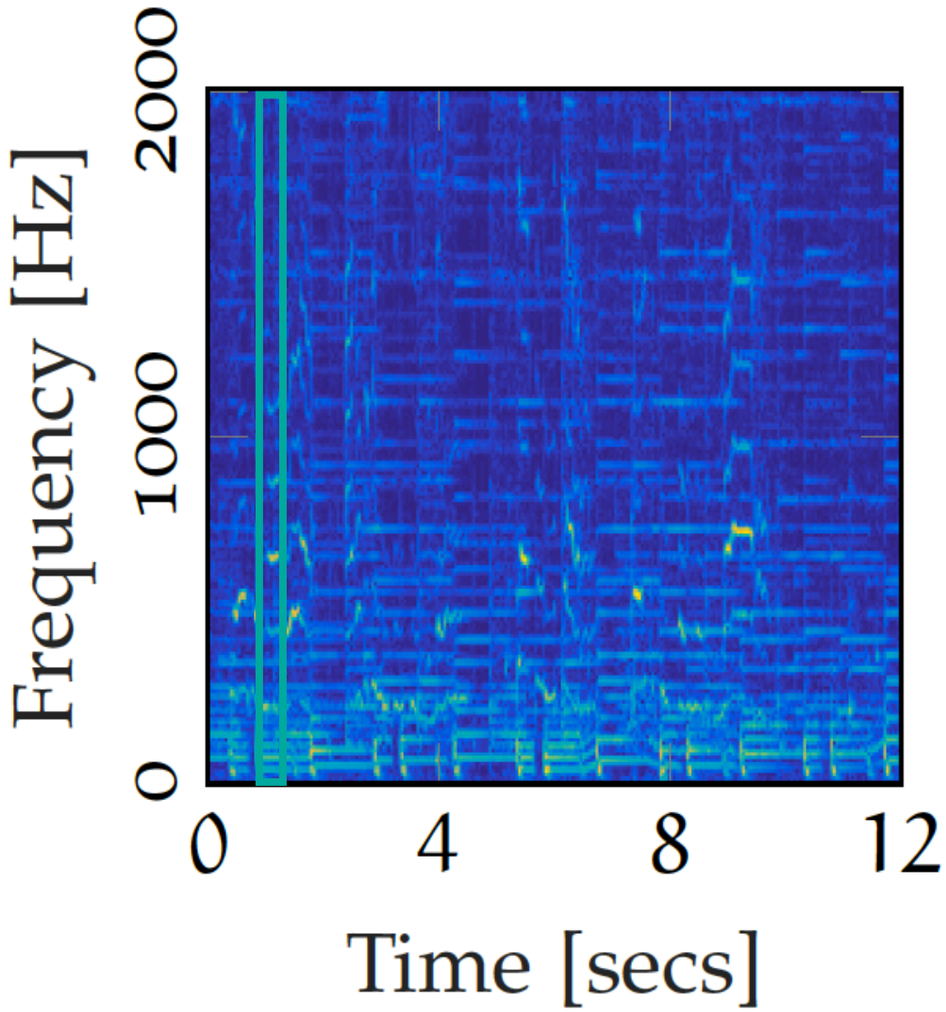
0
1000
2000
3000
4000
5000
Frequency (Hz)

0
1000
2000
3000
4000
5000
Frequency (Hz)

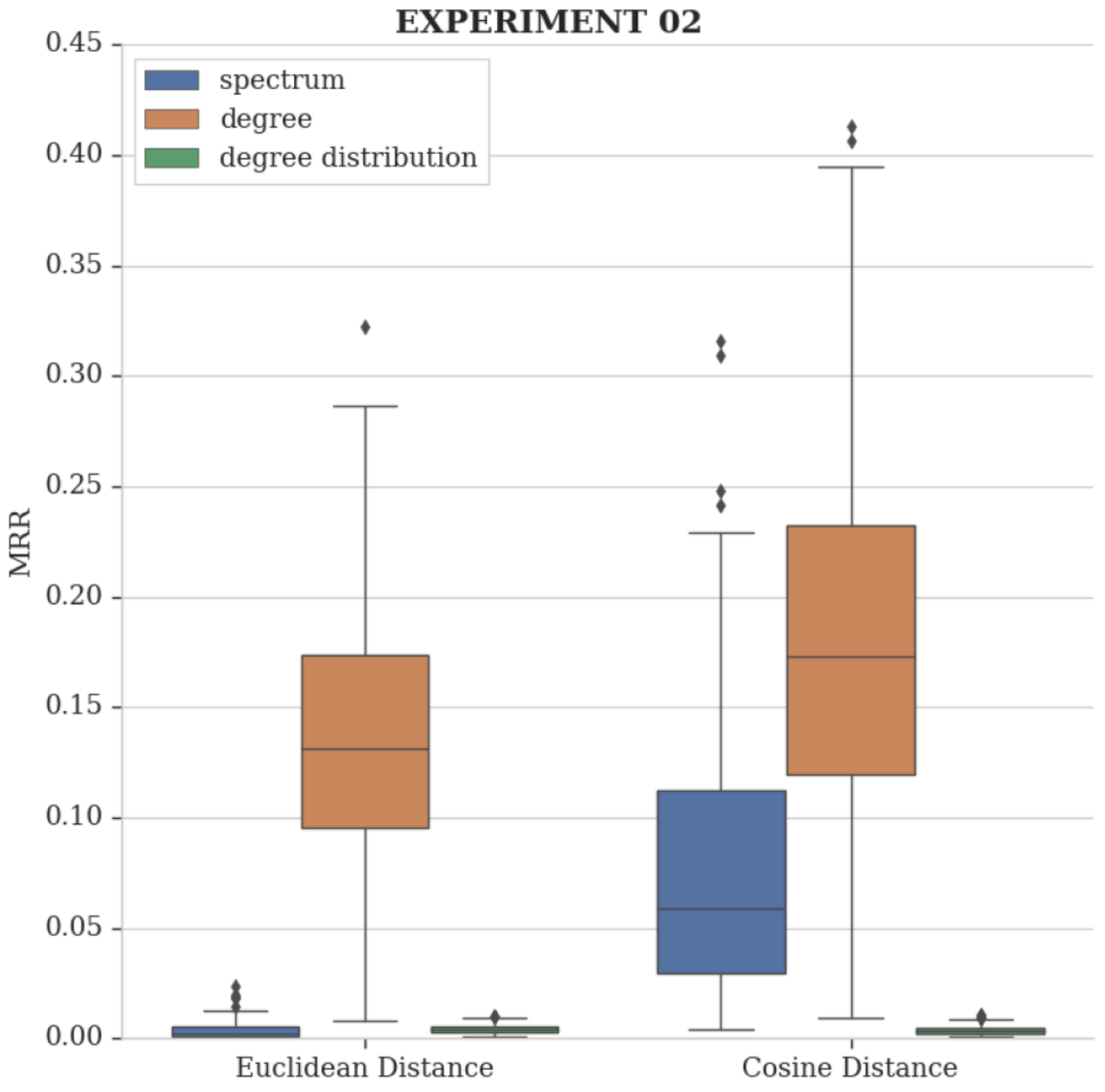
0
1000
2000
3000
4000
5000
Frequency (Hz)


EXPERIMENT 01
Euclidean Distance
Cosine Distance
MRR
1.0
0.8
0.6
0.4
0.2
0.0
-24.0
-12.0
-6.0
-3.0
0.0
3.0
6.0
SNR in dB
spectrum
degree
degree distribution

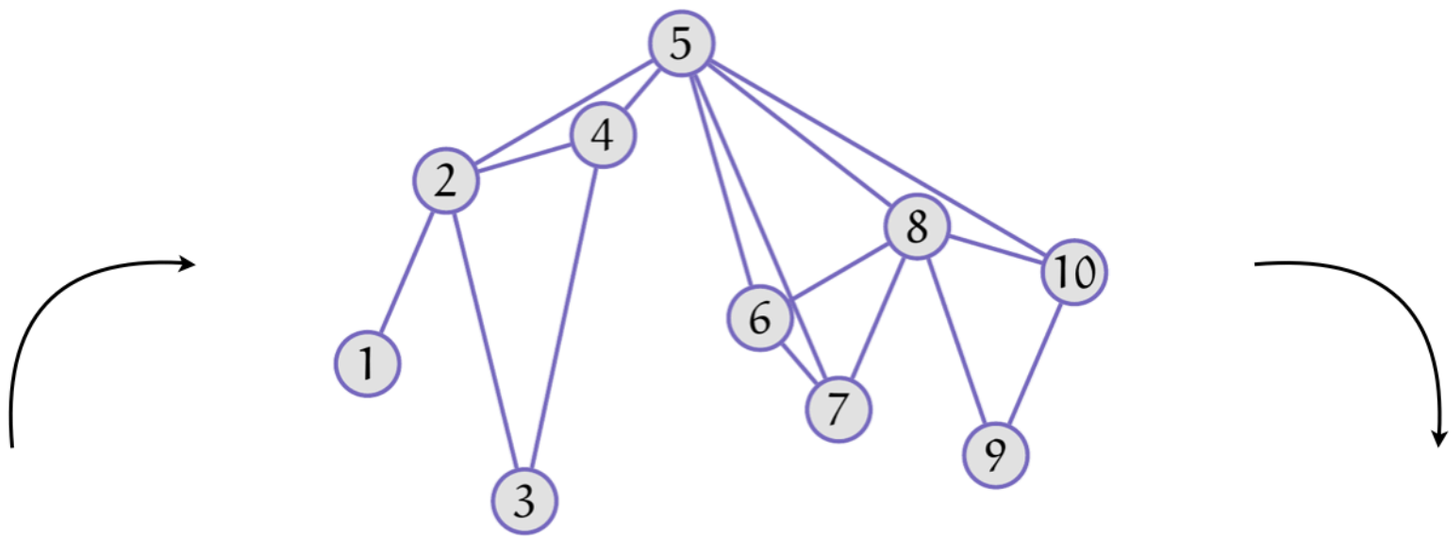


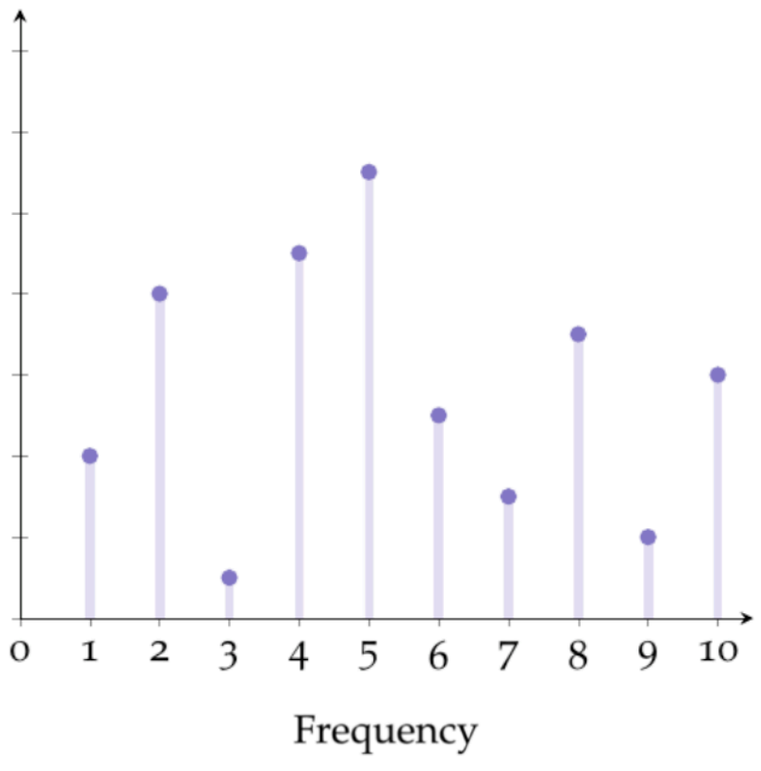


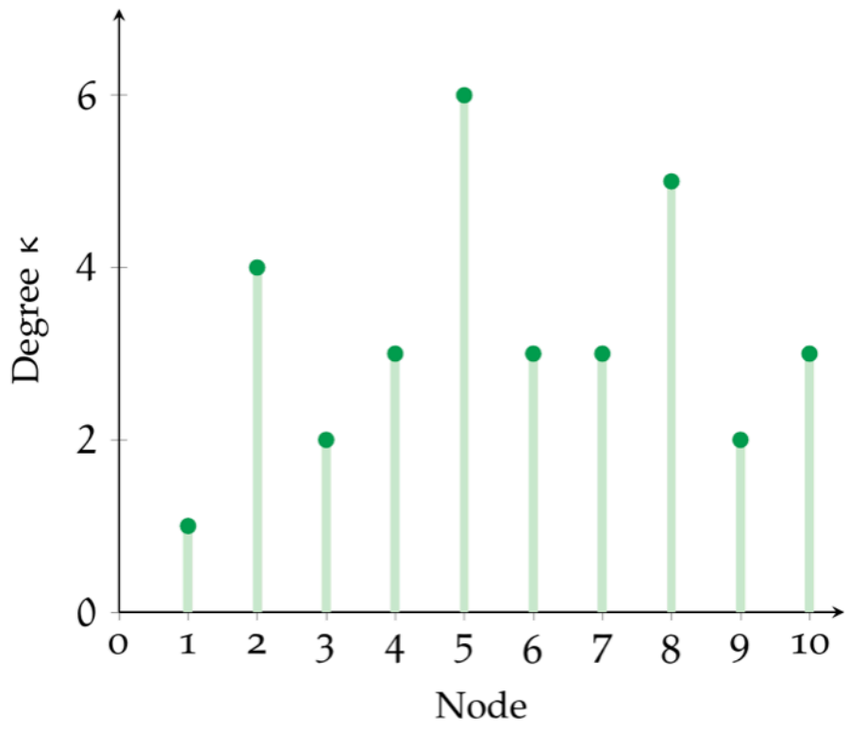
Demixing Secrets Dataset 100 (DSD100)


EXPERIMENT 02
spectrum
degree
degree distribution
MRR
0.45
0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
Euclidean Distance
Cosine Distance

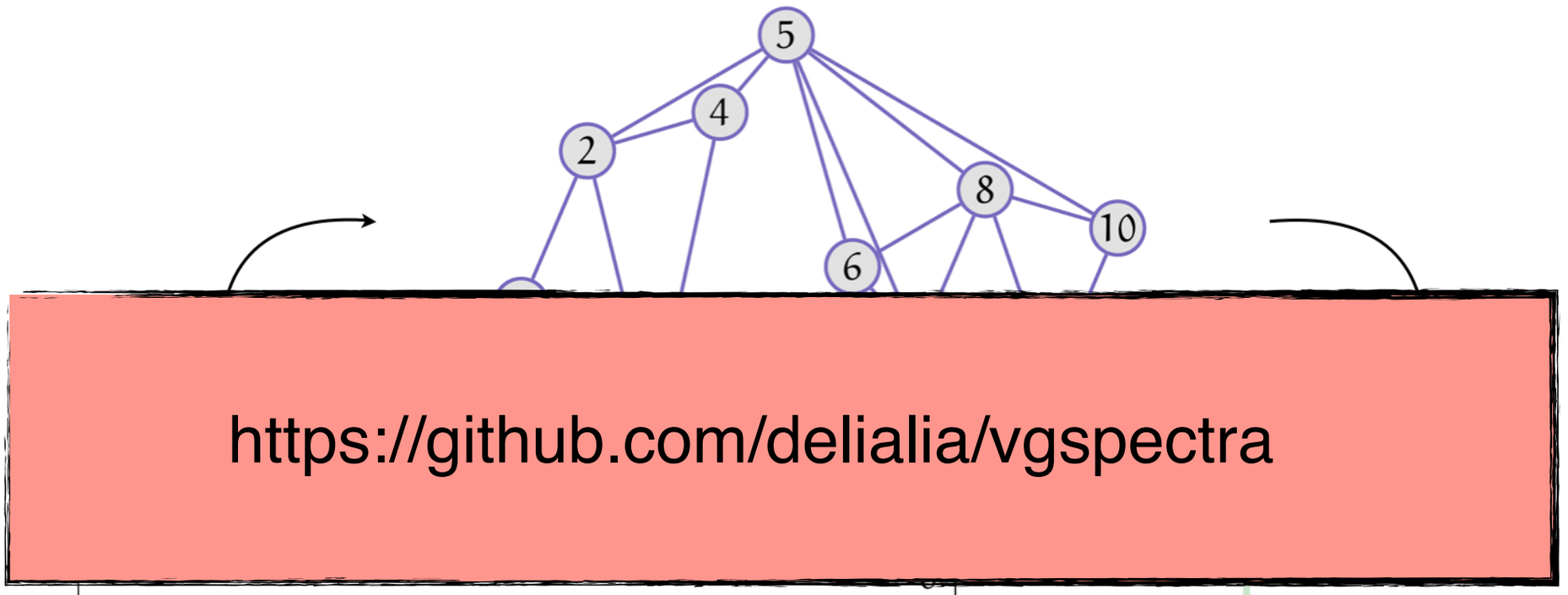
SPECTRAL VISIBILITY GRAPHS



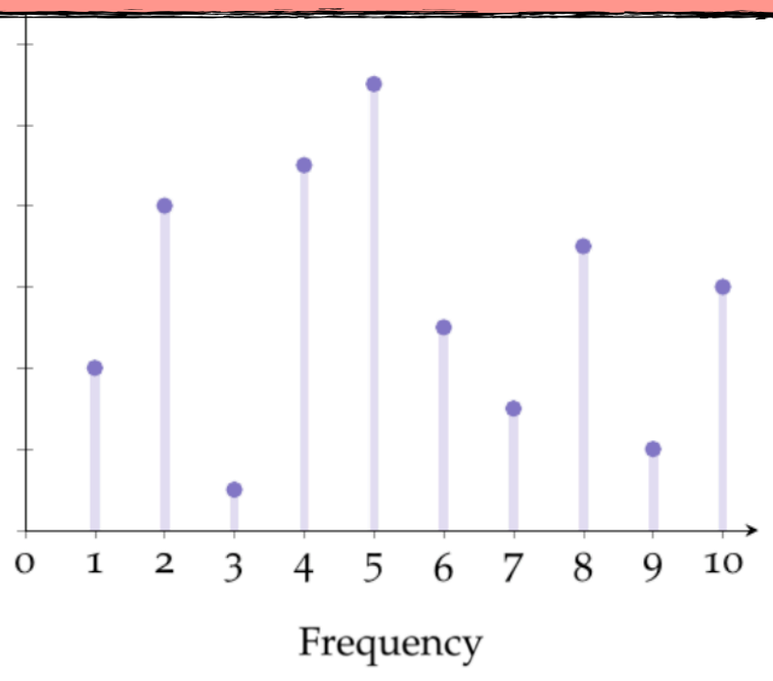


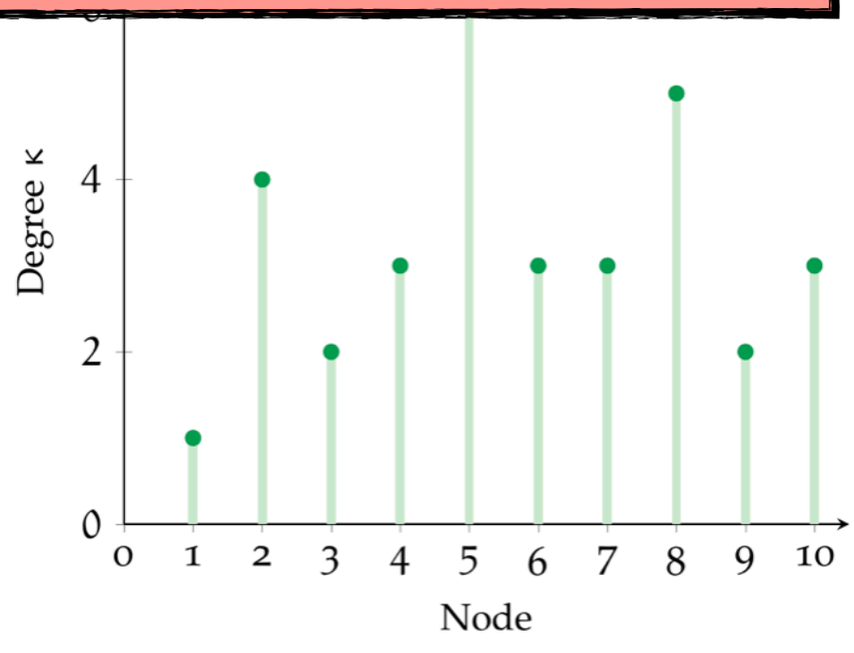


SPECTRAL VISIBILITY GRAPHS

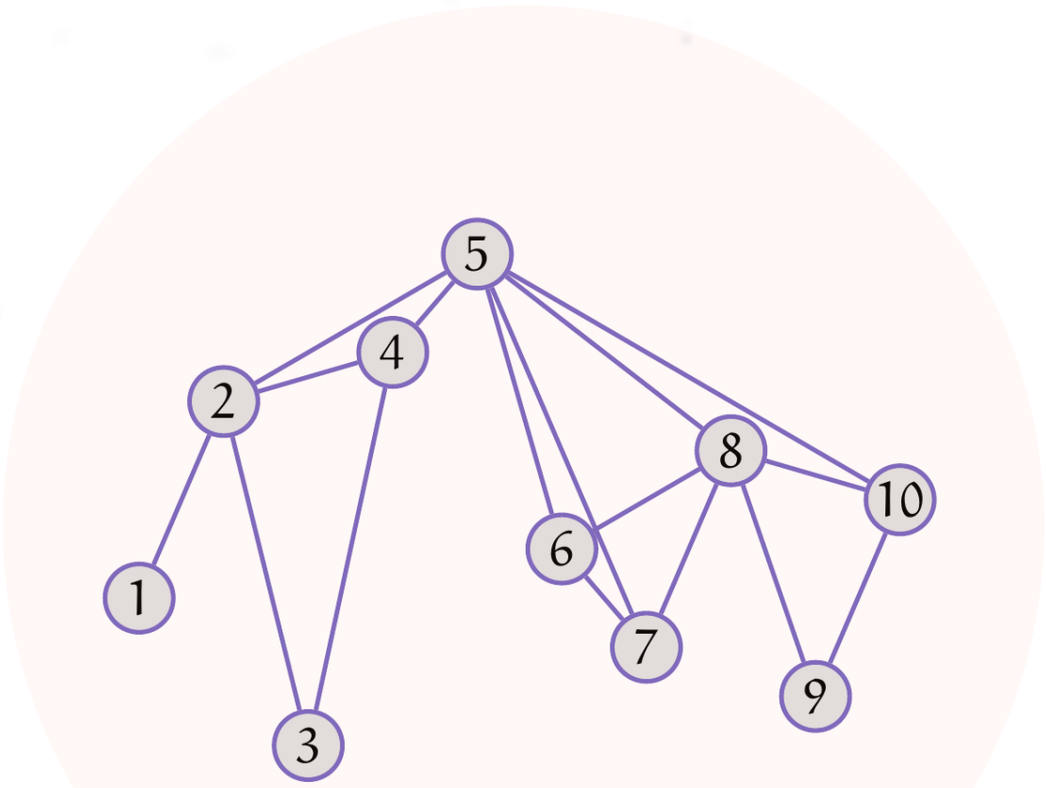


https://github.com/delialia/vgspectra





ANY QUESTIONS ?



https://github.com/delialia/vgspectra