Cancer Metastasis Networks

Presented by

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Introduction

In broader terms:

- Cancer is still at large
- Research is ongoing
- Modelling can improve survival rates

Background:

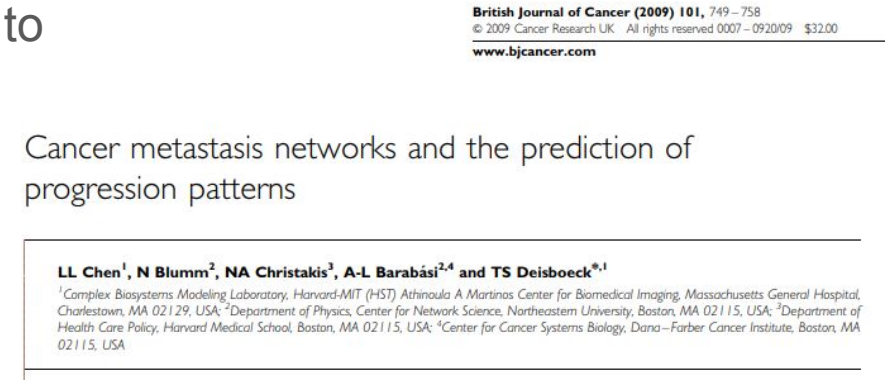
- Cancer and its spread
- Showing the patterns of metastasis
- Early location and treatment

Metastasis Paper

Purpose

- Generate cancer metastasis network to predict progression patterns

- Predicts both:
  - Metastases based on initial tumour
  - Tumour based on set of metastasis sites



British Journal of Cancer (2009) 101, 749 – 758

www.bjcancer.com

Cancer metastasis networks and the prediction of progression patterns

LL Chen[1], N Blumm[2], NA Christakis[3], A-L Barabási[2,4] and TS Deisboeck*,[1]

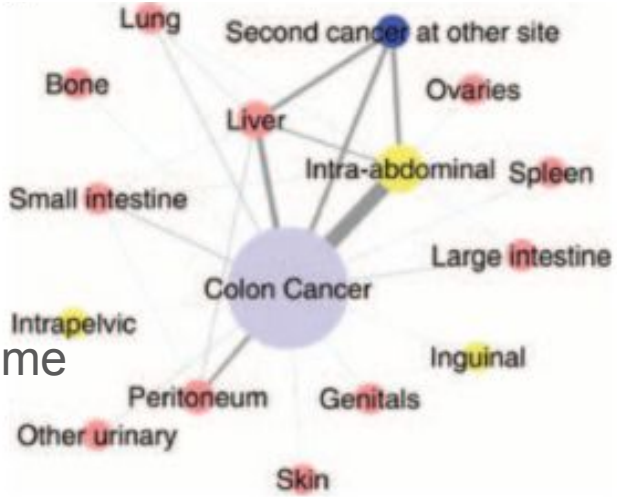
[1]Complex Biosystems Modeling Laboratory, Harvard-MIT (HST) Athinoula A Martinos Center for Biomedical Imaging, Massachusetts General Hospital, Charlestown, MA 02129, USA; [2]Department of Physics, Center for Network Science, Northeastern University, Boston, MA 02115, USA; [3]Department of Health Care Policy, Harvard Medical School, Boston, MA 02115, USA; [4]Center for Cancer Systems Biology, Dana–Farber Cancer Institute, Boston, MA 02115, USA

Construction of Cancer Metastasis Networks

Differences between our implementation and the paper

- Paper: Use dataset from Medicare. Roughly 2 million entries
- Our: Use extremely small database. Roughly 20,000 entries. Less than half with cancer metastasis
- Paper: Has data from patients over a long period of time
- Our: Only has data from patients at one time

Construction of Cancer Metastasis Network



- Generated through data over a period of time
- Censored patients by overall follow-up time
- Nodes represent a primary tumour type
- Size of node represents hazard or incidence
- Links measured by co-occurrence at every point in time
- Co-Occurrence quantified by:
  - Phi-correlation
  - Relative risk
- Our implementation only shows networks at one point in time
- Unable to predict progression patterns

Method

Read in Data | Defining Edges | Models

Filter out unnecessary information

Count instances of:

- Tumour
- Metastasis
- Pairs

Edge represents

<u>Edge weights:</u>

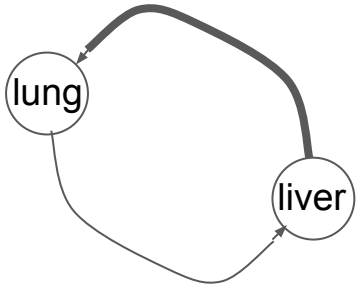
Fractional probability

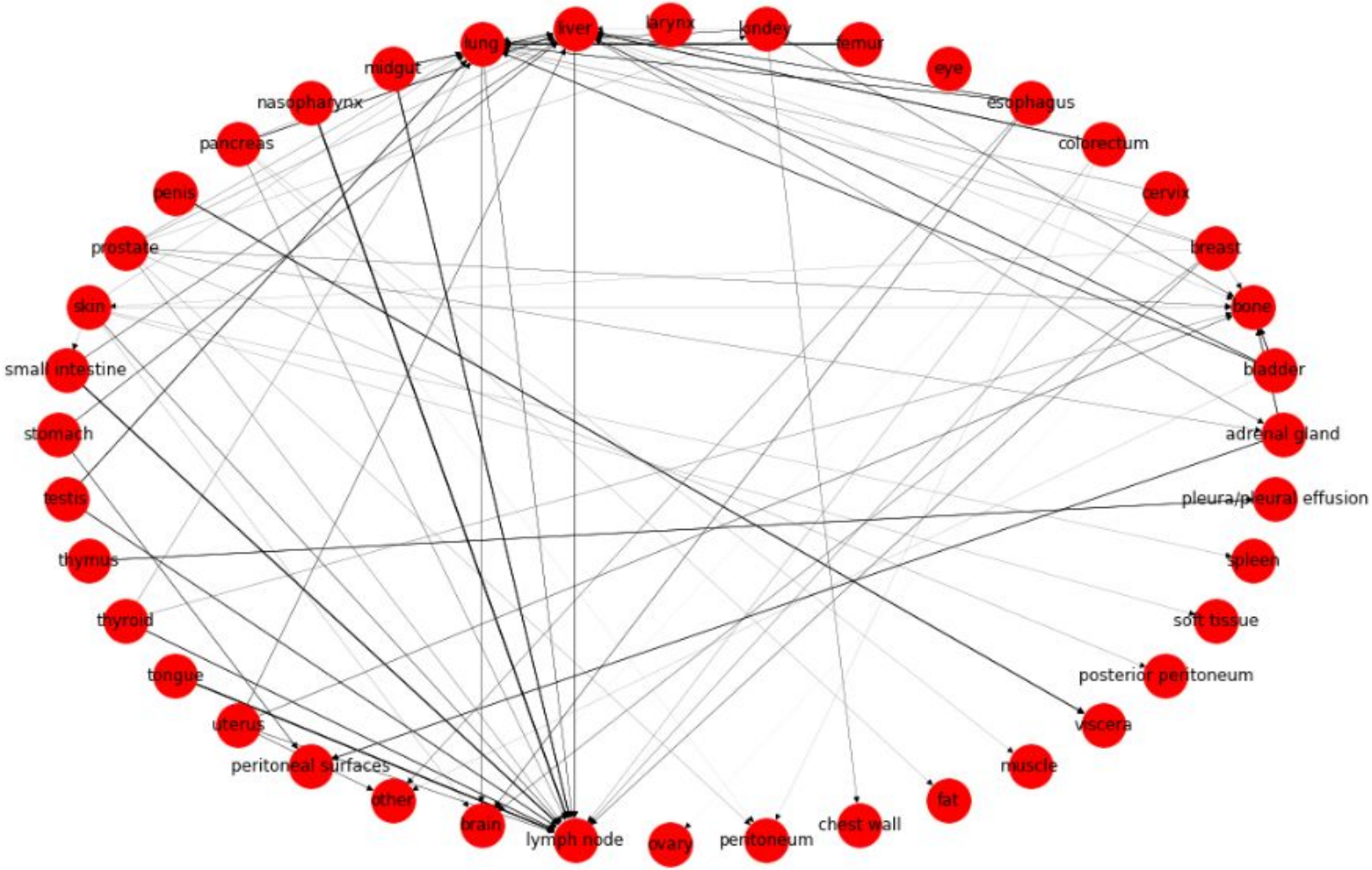
- Use historical data to obtain probability

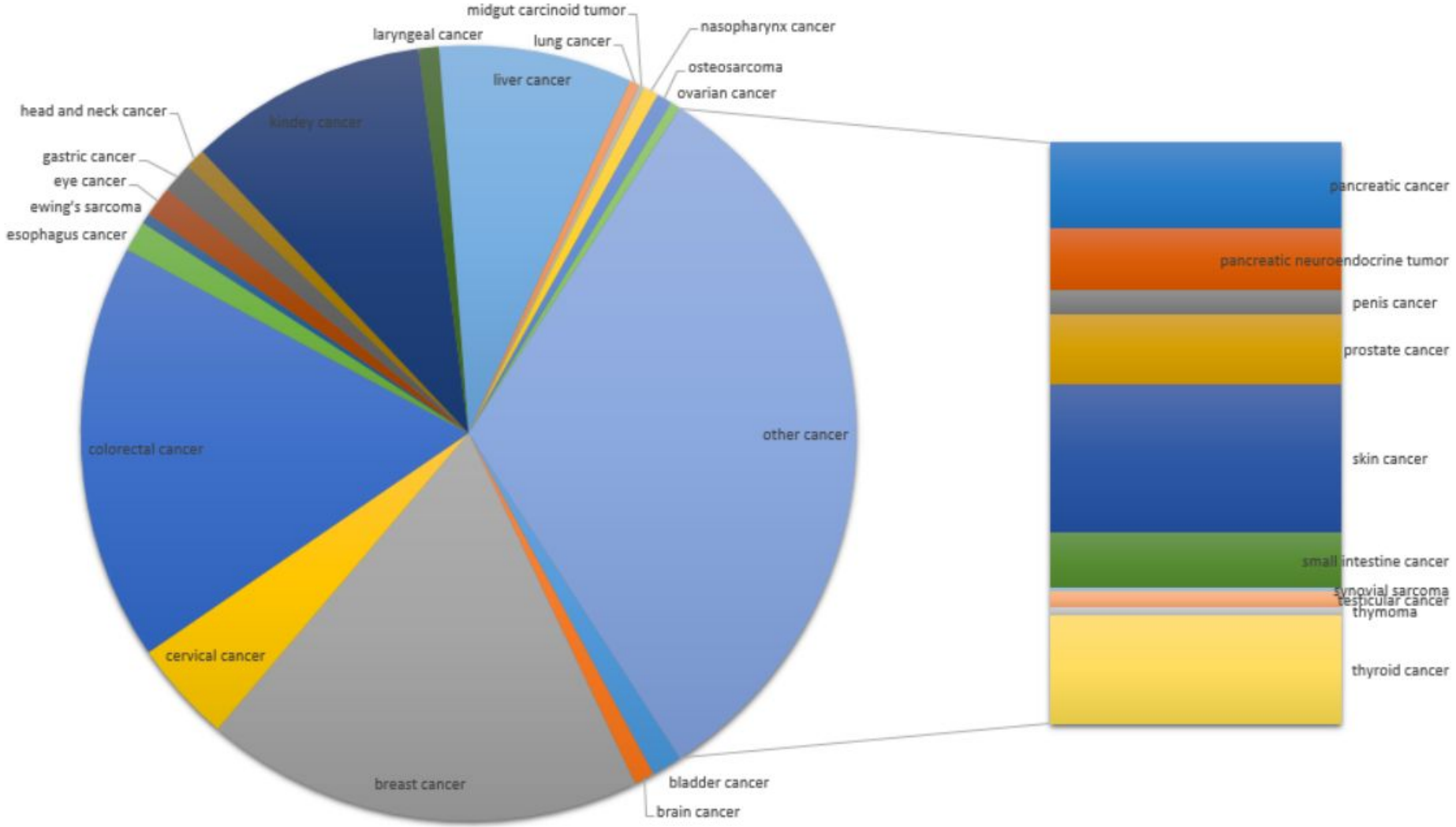
Correlation coefficient

- More complex
  - O(n^3)
- Equally effective

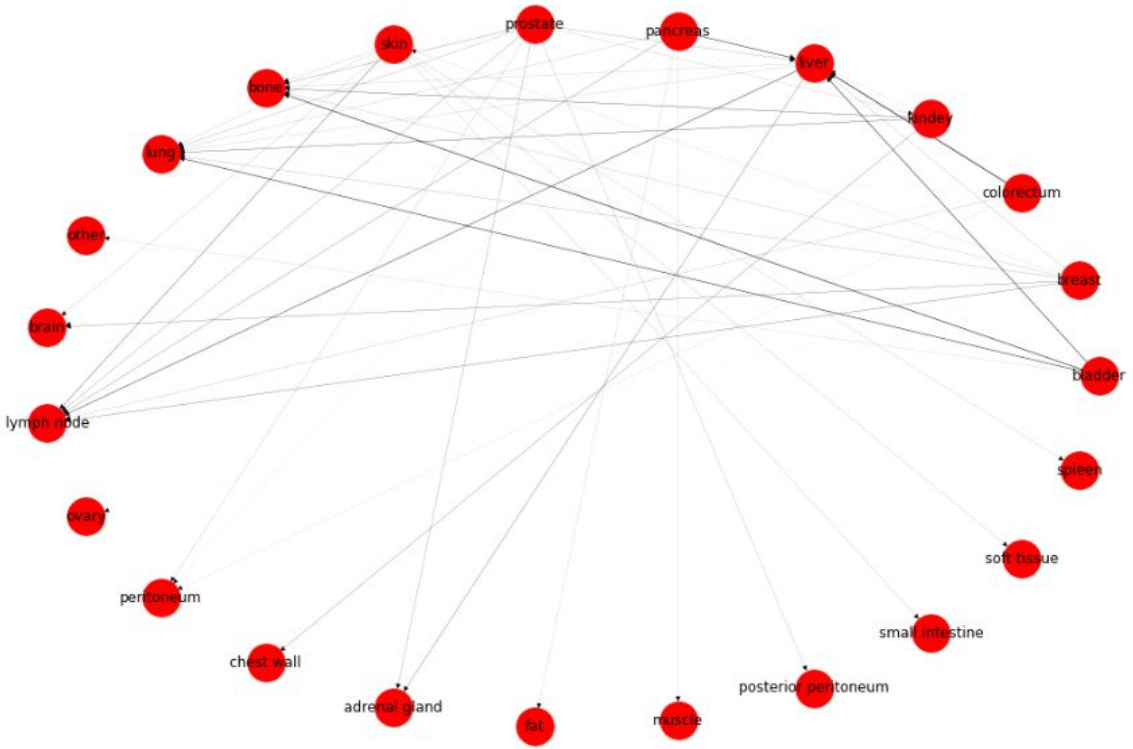
Directed multigraph

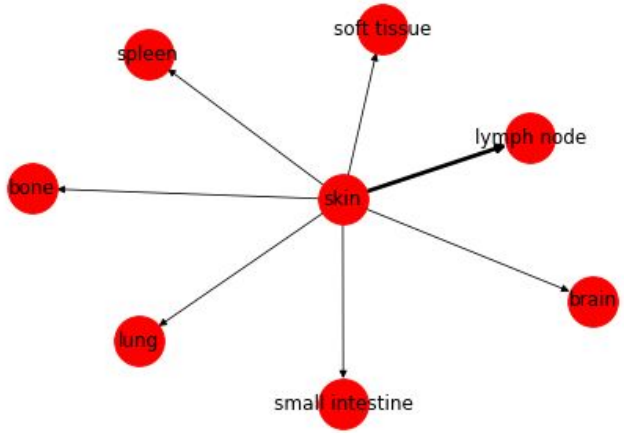


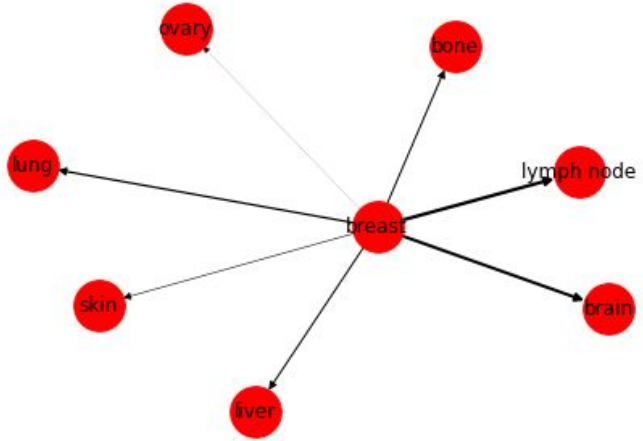

liver
larynx
kidney
femur
eye
esophagus
colorectum
cervix
breast
bone
bladder
adrenal gland
pleura/pleural effusion
spleen
soft tissue
posterior peritoneum
viscera
muscle
fat
chest wall
peritoneum
ovary
lymph node
brain
other
peritoneal surfaces
uterus
tongue
thyroid
thymus
testis
stomach
small intestine
skin
prostate
penis
pancreas
nasopharynx
midgut
lung

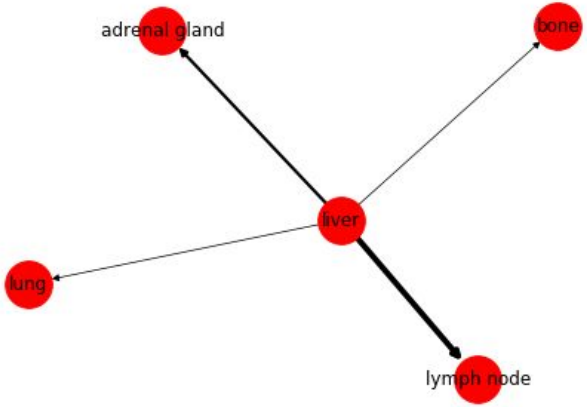

midgut carcinoid tumor
laryngeal cancer
lung cancer
nasopharynx cancer
osteosarcoma
ovarian cancer
liver cancer
kindey cancer
head and neck cancer
gastric cancer
eye cancer
ewing's sarcoma
esophagus cancer
colorectal cancer
other cancer
cervical cancer
breast cancer
bladder cancer
brain cancer
pancreatic cancer
pancreatic neuroendocrine tumor
penis cancer
prostate cancer
skin cancer
small intestine cancer
synovial sarcoma
testicular cancer
thymoma
thyroid cancer

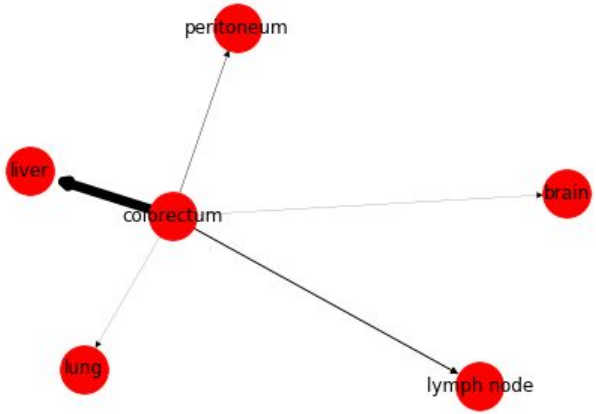
Thresholded Data




soft tissue
spleen
lymph node
bone
skin
brain
lung
small intestine

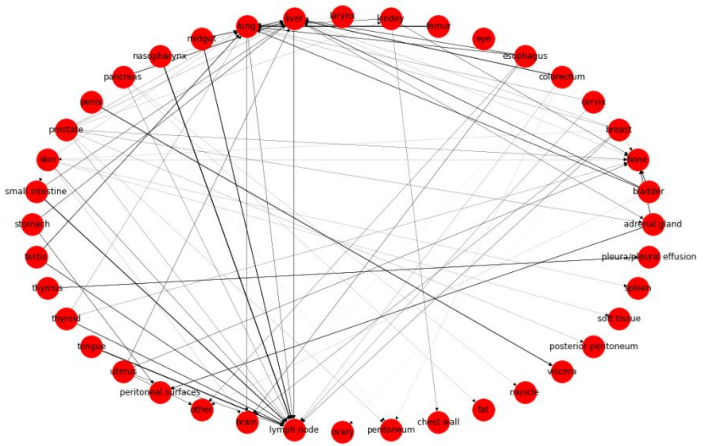

ovary
bone
lung
lymph node
breast
skin
brain
liver

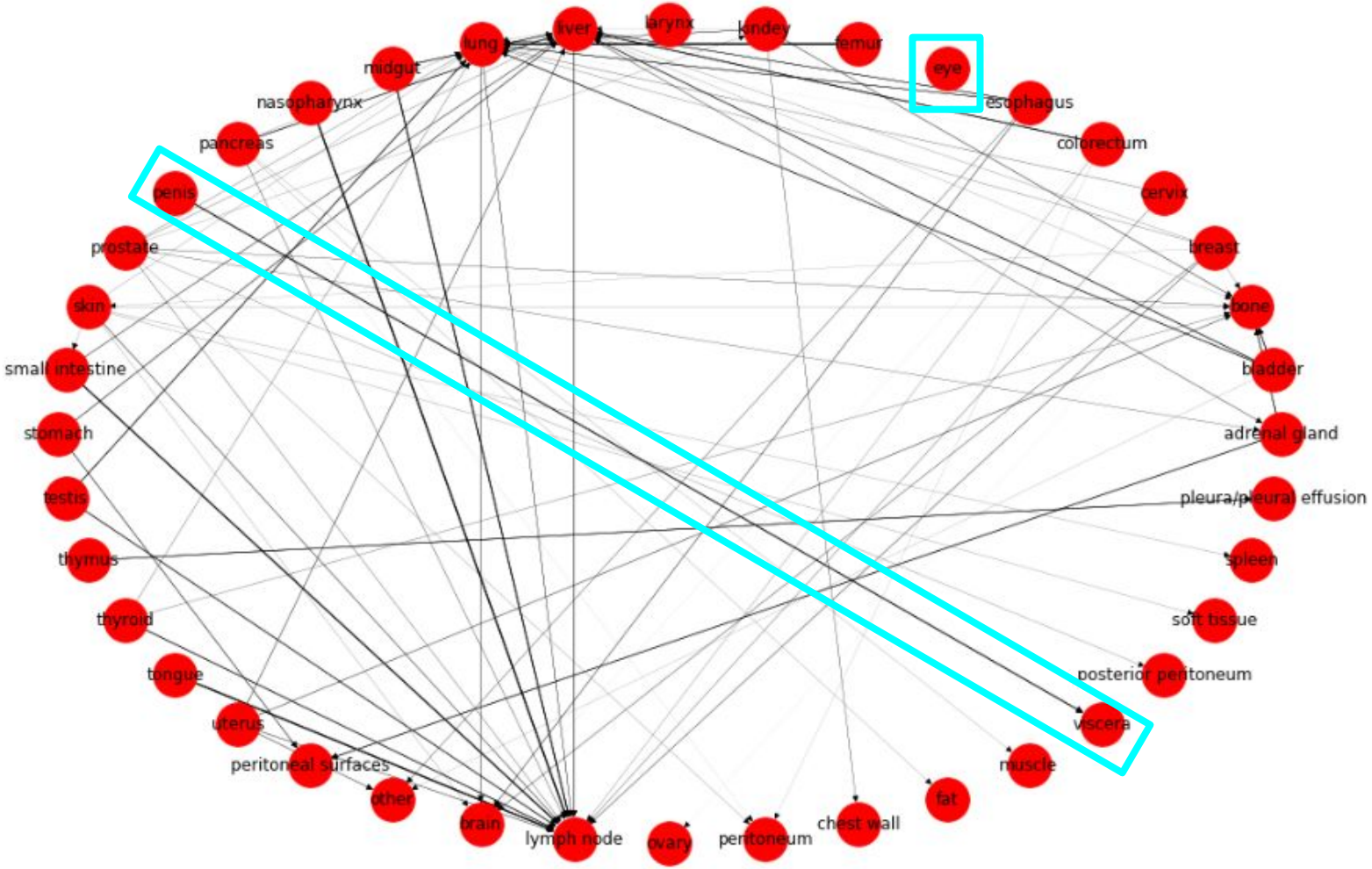

adrenal gland
bone
liver
lung
lymph node


peritoneum
liver
brain
colorectum
lung
lymph node

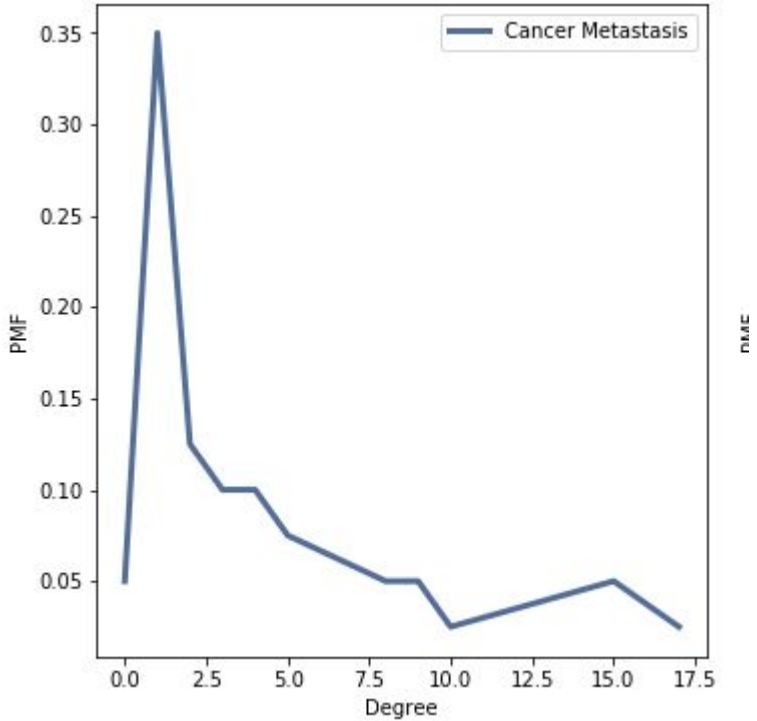
Graph Properties

- Number of nodes: 40
- Clustering coefficient: 0.245
- Average path length: N/A
  - Directed edges
  - Disconnected subsections in graph
  - Isolated nodes e.g. eyes

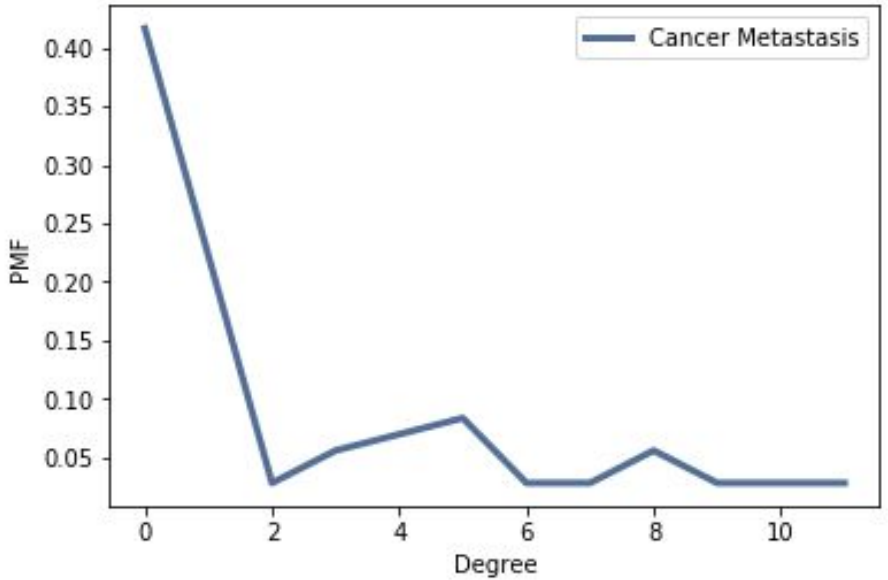



liver
larynx
kidney
femur
lung
eye
midgut
esophagus
nasopharynx
colorectum
pancreas
cervix
penis
breast
prostate
bone
skin
bladder
small intestine
adrenal gland
stomach
pleura/pleural effusion
testis
spleen
thymus
soft tissue
thyroid
posterior peritoneum
tongue
viscera
uterus
muscle
peritoneal surfaces
fat
other
chest wall
brain
lymph node
ovary
peritoneum

Power Law

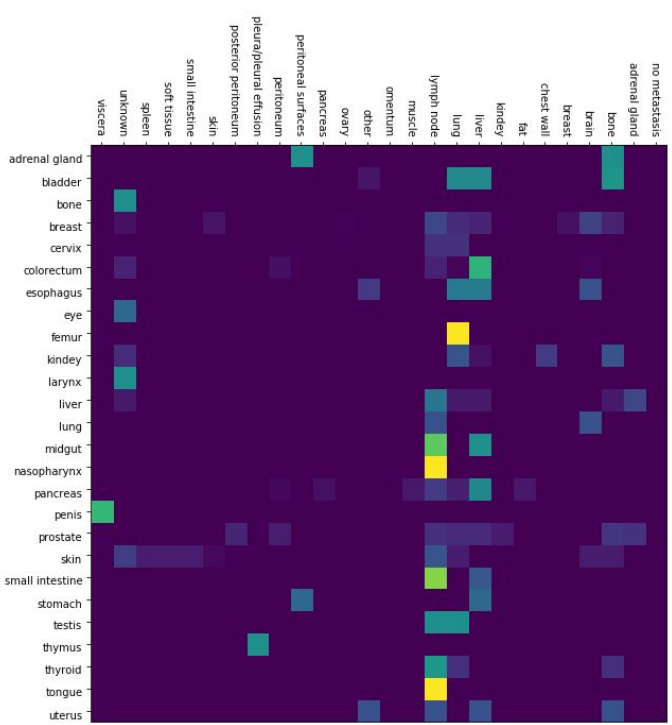


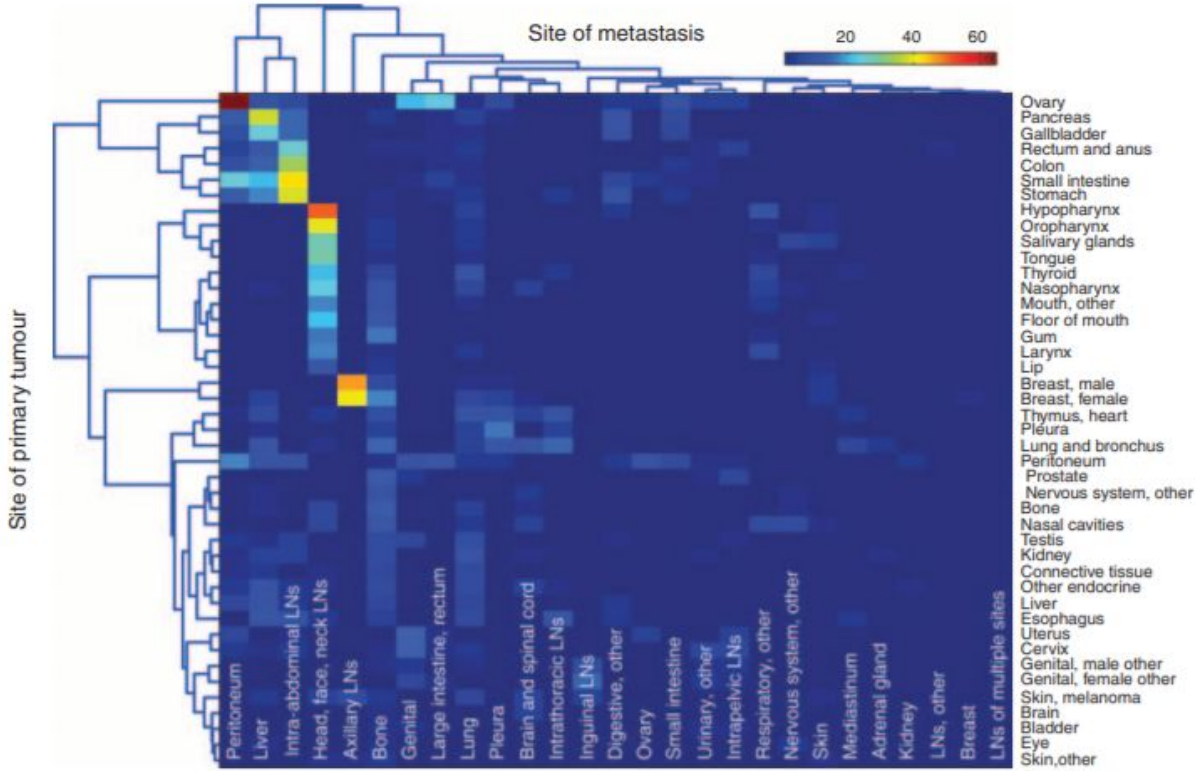
Raw Data



Thresholded Data

Clustergrams





Conclusion

What we have covered:

- Emerging patterns of spread
- Metastasis distributions
- Similarities with familiar models

Future work:

- Higher-quality data for more in-depth research
- More sophisticated/refined model for existing patterns
- Precise prediction of spread or origin