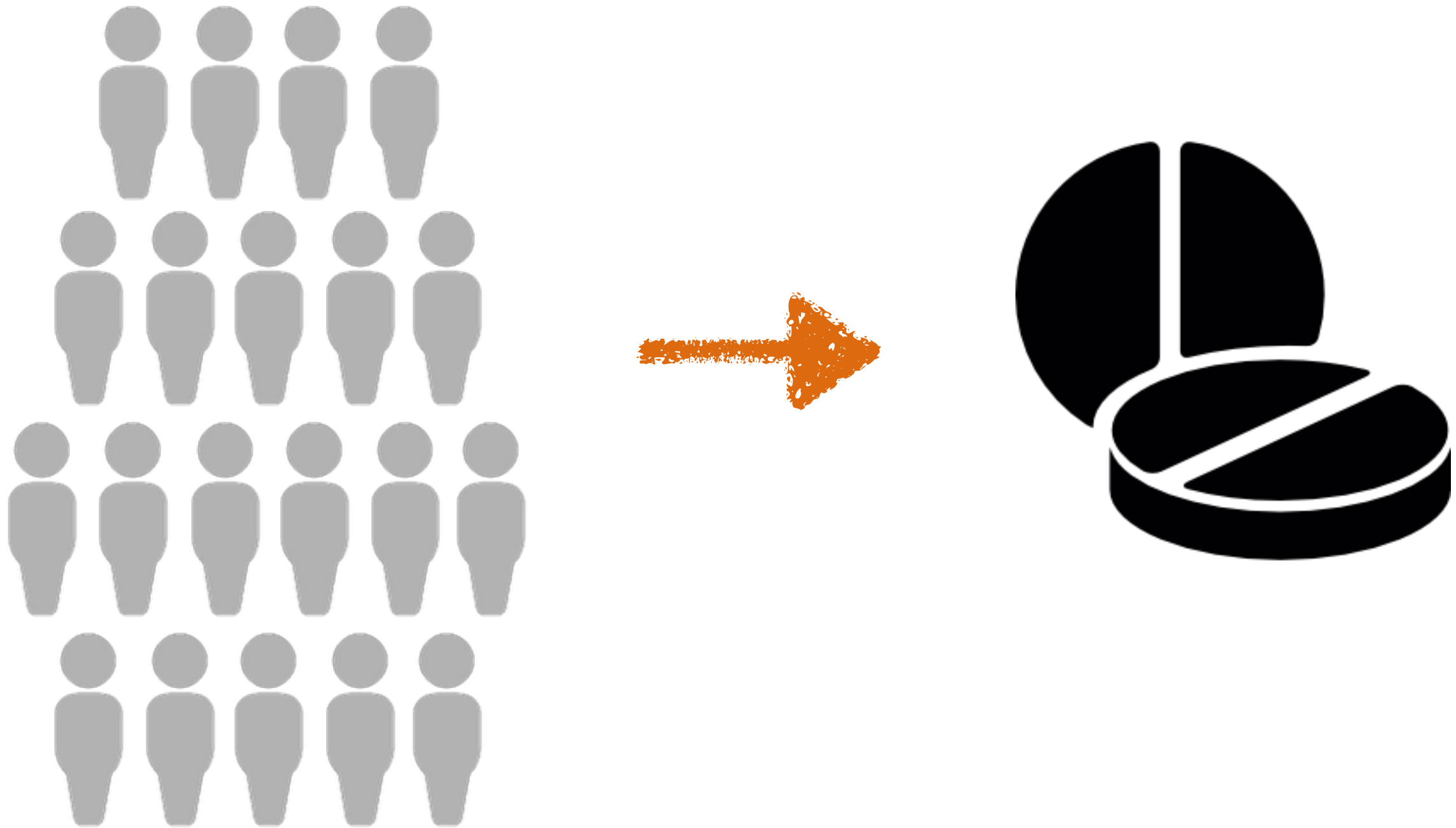


Understanding cancer behaviour with F#

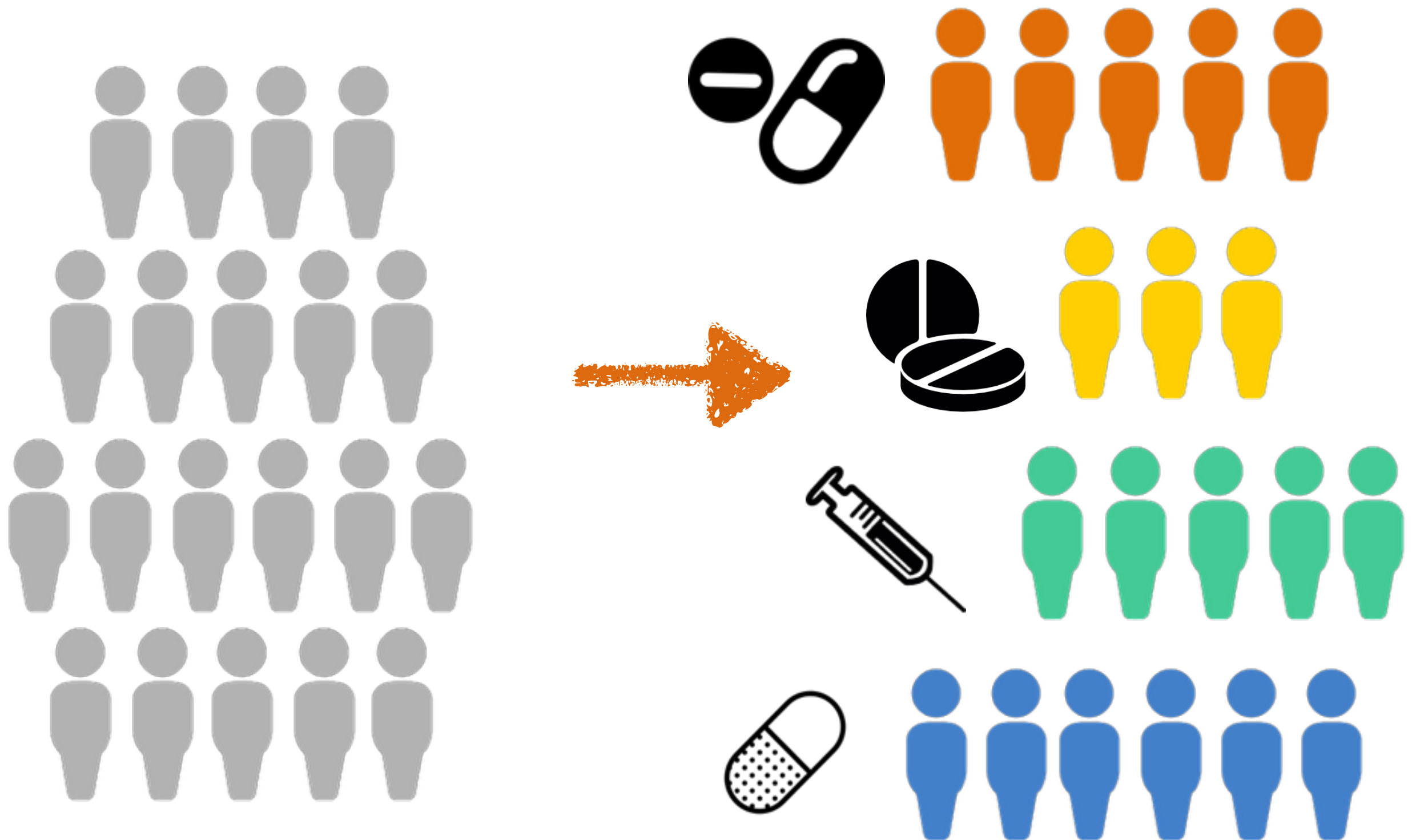
Evelina Gabasova

MRC Biostatistics Unit
University of Cambridge

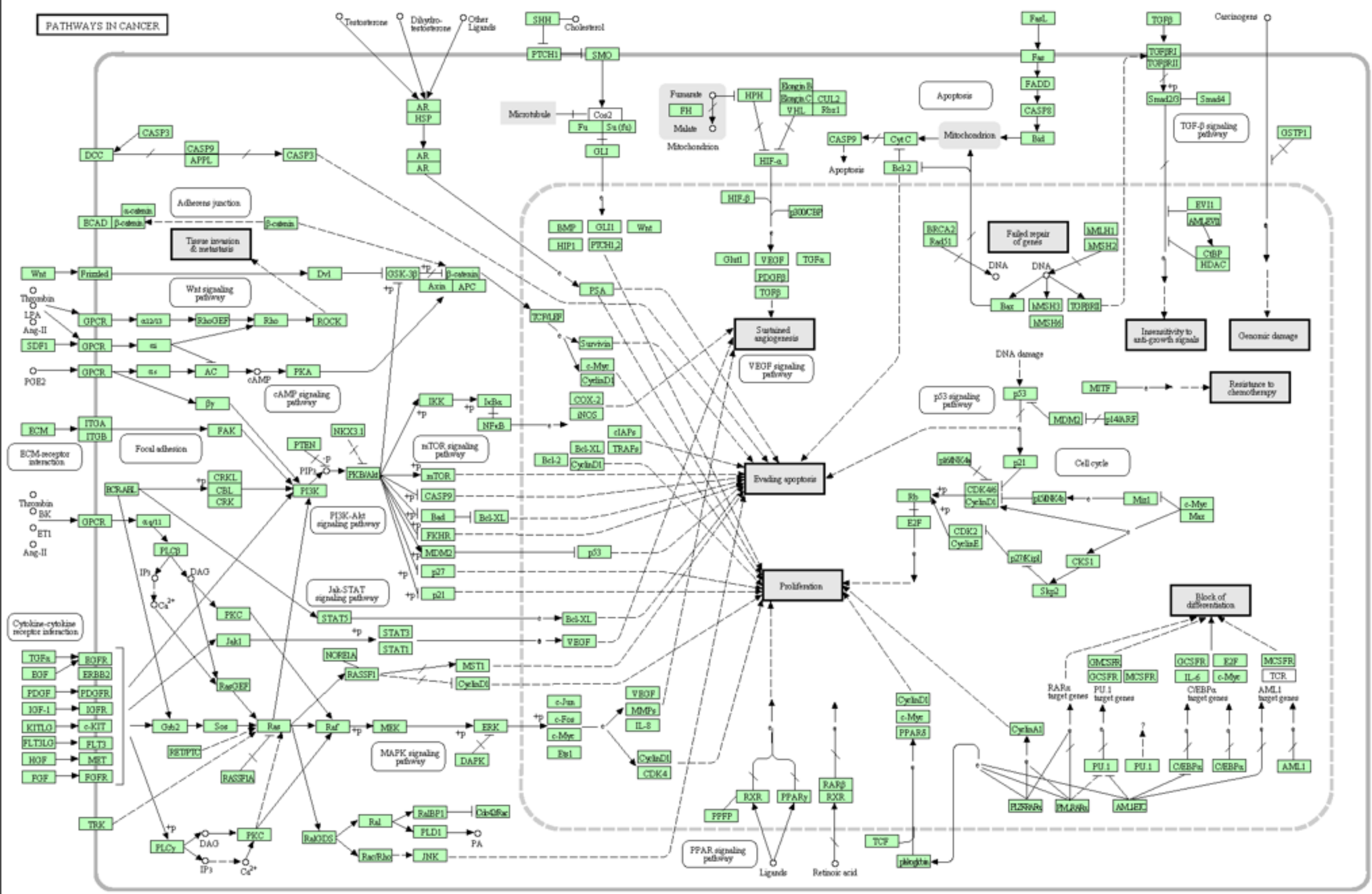
Precision medicine



Precision medicine

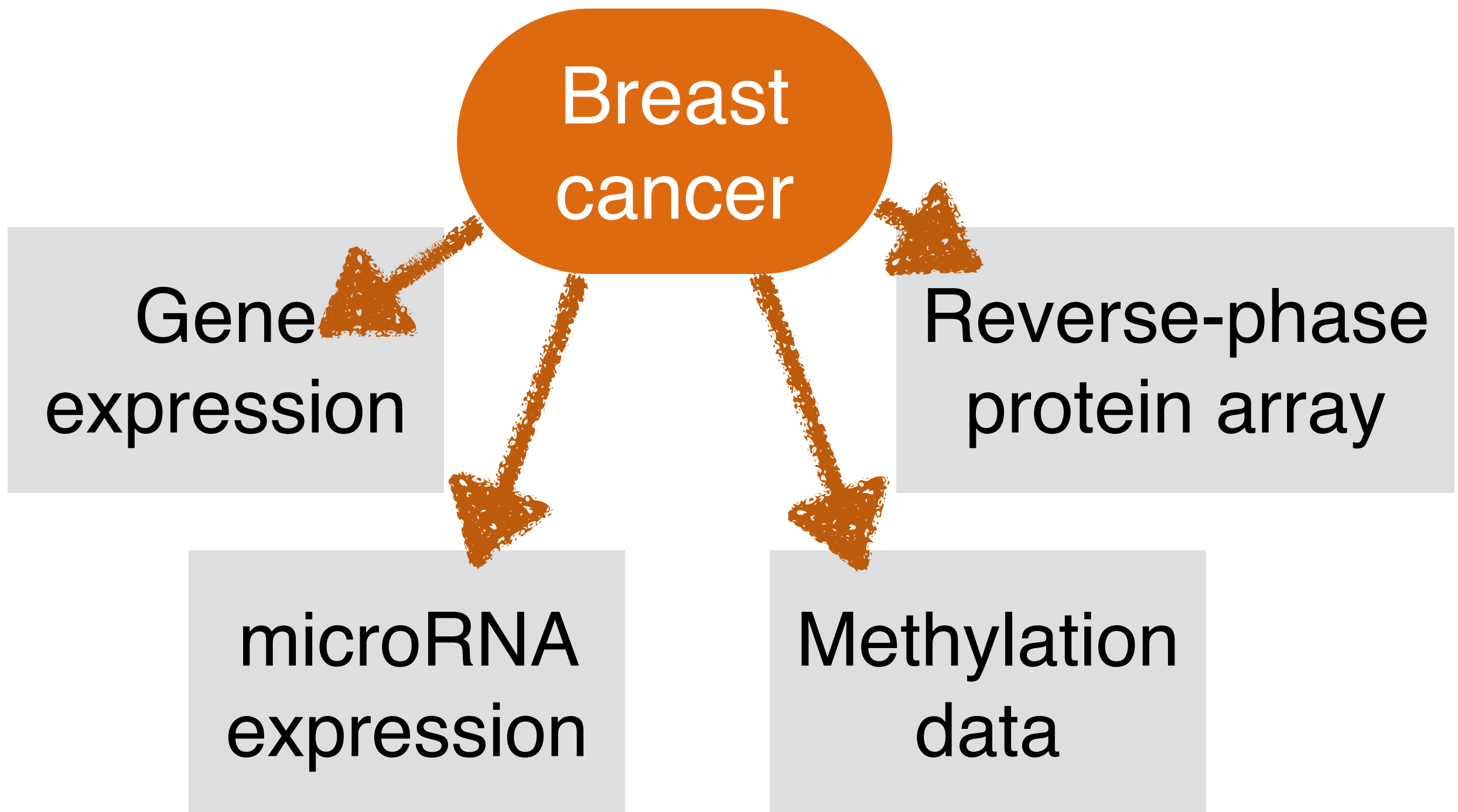


PATHWAYS IN CANCER

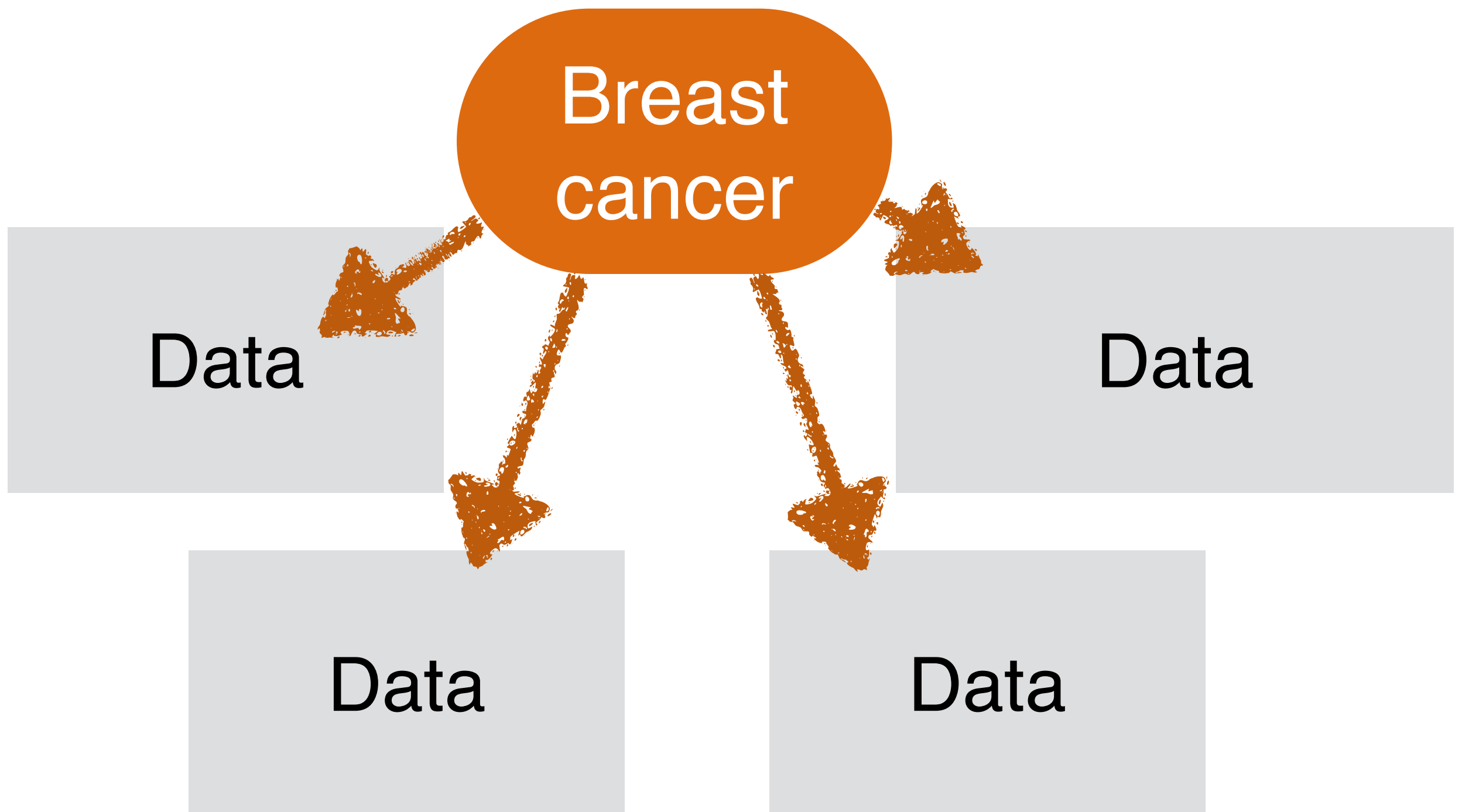


- Colorectal cancer
- Pancreatic cancer
- Osteoma
- Thyroid cancer
- Acute myeloid leukemia
- Chronic myeloid leukemia
- Basal cell carcinoma
- Melanoma
- Renal cell carcinoma
- Bladder cancer
- Prostate cancer
- Endometrial cancer
- Small cell lung cancer
- Non-small cell lung cancer

Integrative clustering



Integrative clustering



Scientific programming

Scripting languages

fast prototyping, easy to use

R, Python, Matlab

Why F#?

```
Lp = lapply(logL, exp)
for(m in 1:M) {
  for(i in 1:N) L[[m]][i,] = rmultinom(1,1,Lp[[m]][i,]) #Generate L from Lp
  if(w>1) L[[m]] = AlignClusters(C,L[[m]], type = 'mat') #Helps to align indices
  n[m,] = colSums(L[[m]])
  for(k in 1:K){ ###Update cluster parameters based on normal-gamma distribution
    if(d[m]==1&n[m,k]>1){
      S[[m]][,k] = sd(X[[m]][,L[[m]][,k]==1])^2
      PostMean = sum(X[[m]][,L[[m]][,k]==1])/(n[m,k]+1)
      B[[m]][,k] = b0[[m]]+0.5*(n[m,k]*S[[m]][,k]+n[m,k]*(mean(X[[m]][,L[[m]][,k]==1))-mu0
    if(d[m]>1&n[m,k]>1){
      PostMean = (mu0[[m]]+rowSums(X[[m]][,L[[m]][,k]==1]))/(n[m,k]+1)
      S[[m]][,k] = apply(X[[m]][,L[[m]][,k]==1],MARGIN=1,FUN='sd')^2
    B[[m]][,k] = b0[[m]]+0.5*(n[m,k]*S[[m]][,k]+n[m,k]*(rowMeans(X[[m]][,L[[m]][,k]==1))-mu0
    if(n[m,k]==1){
      PostMean = (mu0[[m]]+X[[m]][,L[[m]][,k]==1])/2
    B[[m]][,k] = b0[[m]]+0.5*(X[[m]][,L[[m]][,k]==1]-mu0[[m]])^2/2}
    if(n[m,k]==0){
      PostMean = mu0[[m]]
      B[[m]][,k] = b0[[m]]}
    Lambda = 1+n[m,k]
    A[[m]][,k] = a0[[m]]+n[m,k]/2
    Tau[[m]][,k] = rgamma(d[m],shape=A[[m]][,k],rate=B[[m]][,k])
    mu[[m]][,k] = rnorm(d[m],PostMean,sqrt(1/(Tau[[m]][,k]*Lambda)))
    Sigma[[m]][,k] = sqrt(1/Tau[[m]][,k])}
  }
```


Why F#?

```
Lp = lapply(logL, exp)
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  for(i in 1:N) L[[m]][i,] = rmultinom(1,1,Lp[[m]][i,]) #Generate L from Lp
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      S[[m]][,k] = apply(X[[m]][,L[[m]][,k]==1],MARGIN=1,FUN='sd')^2
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    if(n[m,k]==1){
      PostMean = (mu0[[m]]+X[[m]][,L[[m]][,k]==1])/2
      B[[m]][,k] = b0[[m]]+0.5*(X[[m]][,L[[m]][,k]==1]-mu0[[m]])^2/2}
    if(n[m,k]==0){
      PostMean = mu0[[m]]
      B[[m]][,k] = b0[[m]]}
    Lambda = 1+n[m,k]
    A[[m]][,k] = a0[[m]]+n[m,k]/2
    Tau[[m]][,k] = rgamma(d[m],shape=A[[m]][,k],rate=B[[m]][,k])
    mu[[m]][,k] = rnorm(d[m],PostMean,sqrt(1/(Tau[[m]][,k]*Lambda)))
    Sigma[[m]][,k] = sqrt(1/Tau[[m]][,k])}
  }
```

Vector? Matrix?

List? Array?

Data frame?

Why F#?

```
25 let newas =
26     data.Contexts
27     |> Array.map (fun context ->
28         let pis = state.ContextWeights.[context]
29         let rawPriorPis = Array.create pis.Length 1.0
30         let value = sampleDirichletConcentration (hyperprior.AlphasPrior.[context])
31         (
32             |> to
33             { state w
34             | FixedValue(
35                 // do not
36                 state
37                 state
38
39 // Context-specific
40 // *****
41
42 // Sample from conditional Dirichlet distribution with random walk Metropolis-Hastings
43 let sampleDirichlet_MetropolisHastings (currentValues: float[])
44     priorConcentration loglikFunction =
45         // 1. Add random walk proposal to current values
46         let randomWalkProposal = Normal(0.0, 1.0, rnd)
47         let proposal_unnorm =
48             currentValues
49             |> Array.map (fun x -> x + 0.1 * randomWalkProposal.Sample())
50
```

val sampleDirichletConcentration :

gammaDist : Gamma ->

rawPriorPis: seq<float> ->

pis : seq<float> ->

sampleType : SampleConcentrationParams

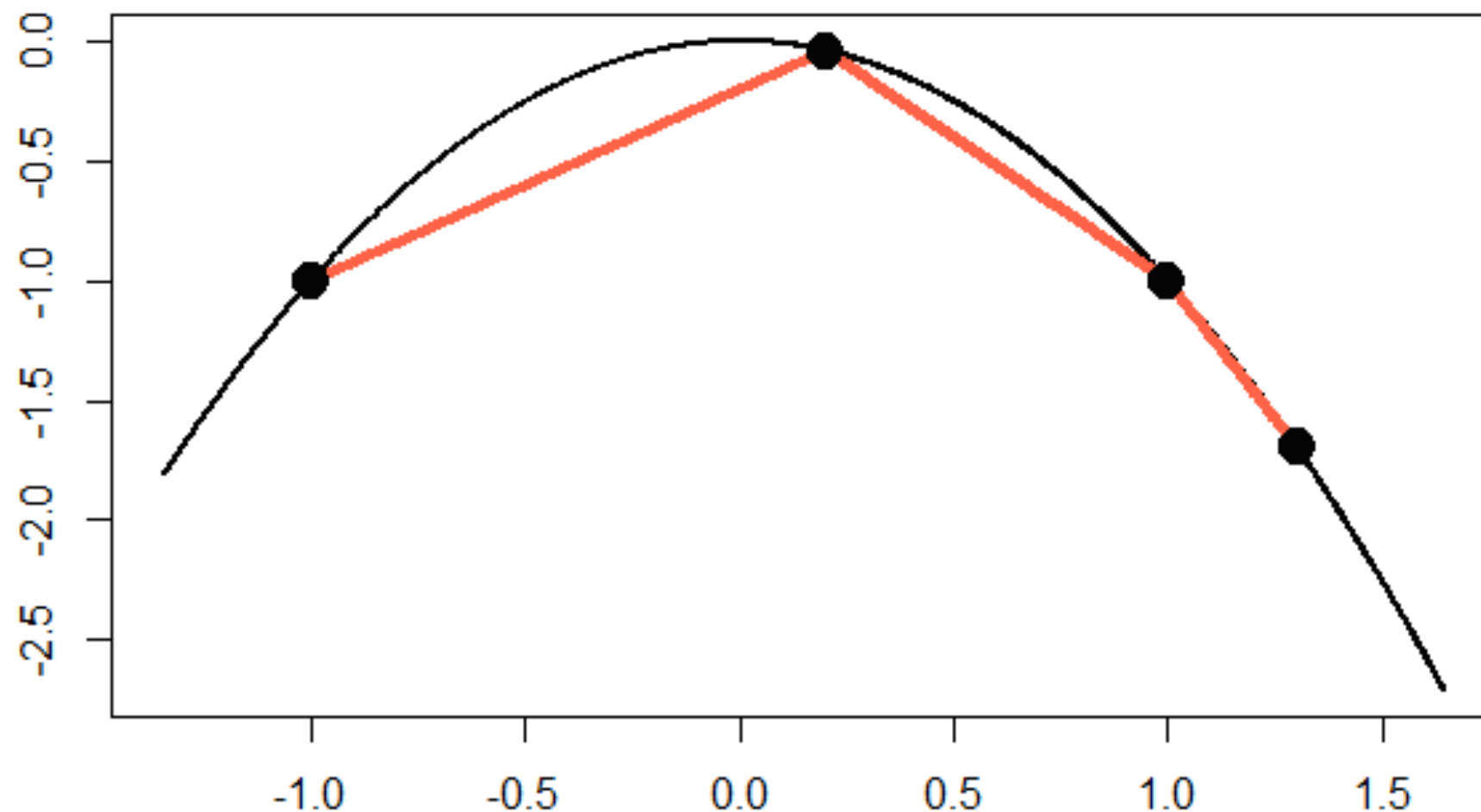
-> float

Summary

Adaptive rejection sampling (derivative-free)

Case study

Rewrite an algorithm from Matlab into F#
adaptive rejection sampling

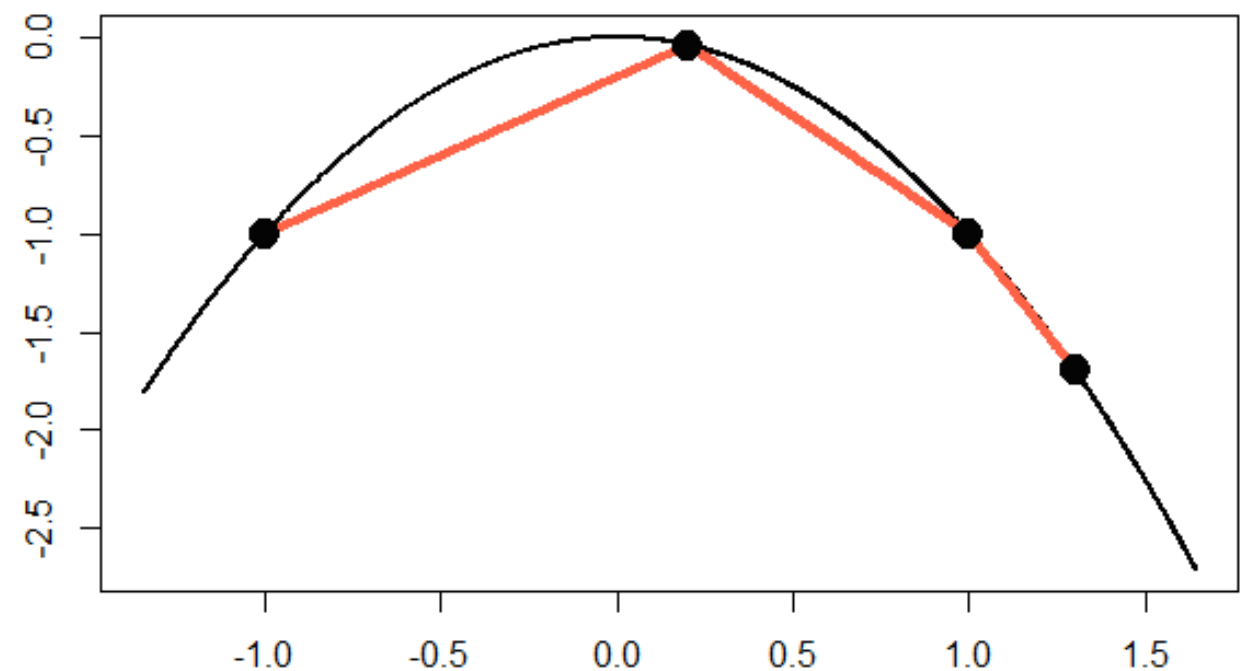


Case study

```
% value of the lower bound
if x < min([lowerHull.left])
    lhVal = -inf;
elseif x > max([lowerHull.right]);
    lhVal = -inf;
else
    for li=1:length(lowerHull)
        left = lowerHull(li).left;
        right = lowerHull(li).right;

        if x >= left && x <= right
            lhVal = lowerHull(li).m*x + lowerHull(li).b;
            break;
        end
    end
end
end
```

MatLab



Pattern matching

```
% value of the lower bound
if x < min([lowerHull.left])
    lhVal = -inf;
elseif x > max([lowerHull.right]);
    lhVal = -inf;
else
    for li = 1:length(lowerHull)
        left = lowerHull(li).left;
        right = lowerHull(li).right;

        if x >= left && x <= right
            lhVal = lowerHull(li).m*x + lowerHull(li).b;
            break;
        end
    end
end
end
```

MatLab

```
// value of the lower bound
let lhVal =
    match (lowerHull, x) with
    | OutsideOnLeft -> -infinity
    | OutsideOnRight -> -infinity
    | InsideInterval lh -> lh.M * x + lh.B
```

F#

Pattern matching

```
% value of the lower bound
if x < min([lowerHull.left])
    lhVal = -inf;
elseif x > max([lowerHull.right]);
    lhVal = -inf;
else
    for li = 1:length(lowerHull)
        left = lowerHull(li).left;
        right = lowerHull(li).right;

        if x >= left && x <= right
            lhVal = lowerHull(li).m*x + lowerHull(li).b;
            break;
        end
    end
end
end
```

MatLab

```
// value of the lower bound
let lhVal =
    match (lowerHull, x) with
    | OutsideOnLeft -> -infinity
    | OutsideOnRight -> -infinity
    | InsideInterval lh -> lh.M * x + lh.B
```

F#

Legibility

$$X + \log \left(\sum_{i=1}^N \exp \{x_i - X\} \right)$$


where $X = \max \{x_i; i = 1, \dots, N\}$

```
let logSumExp xs =  
  let maxValue = Array.max xs  
  xs  
  |> Array.map (fun x -> exp(x - maxValue))  
  |> Array.sum  
  |> log  
  |> (+) maxValue
```

Legibility

$$X + \log \left(\sum_{i=1}^N \exp \{x_i - X\} \right)$$

where $X = \max \{x_i; i = 1, \dots, N\}$


The diagram consists of three red arrows pointing to the left. The longest arrow originates from the 'X' in the definition 'where X = max {x_i; i = 1, ..., N}' and points to the 'X' in the logarithmic term of the equation above. A shorter arrow originates from the 'x_i' in the same definition and points to the 'x_i' in the exponent of the equation. A third, even shorter arrow originates from the 'N' in the definition and points to the 'N' in the summation index of the equation.

```
let logSumExp xs =  
  let maxValue = Array.max xs  
  xs  
  |> Array.map (fun x -> exp(x - maxValue))  
  |> Array.sum  
  |> log  
  |> (+) maxValue
```


Legibility

$$X + \log \left(\sum_{i=1}^N \exp \{x_i - X\} \right)$$

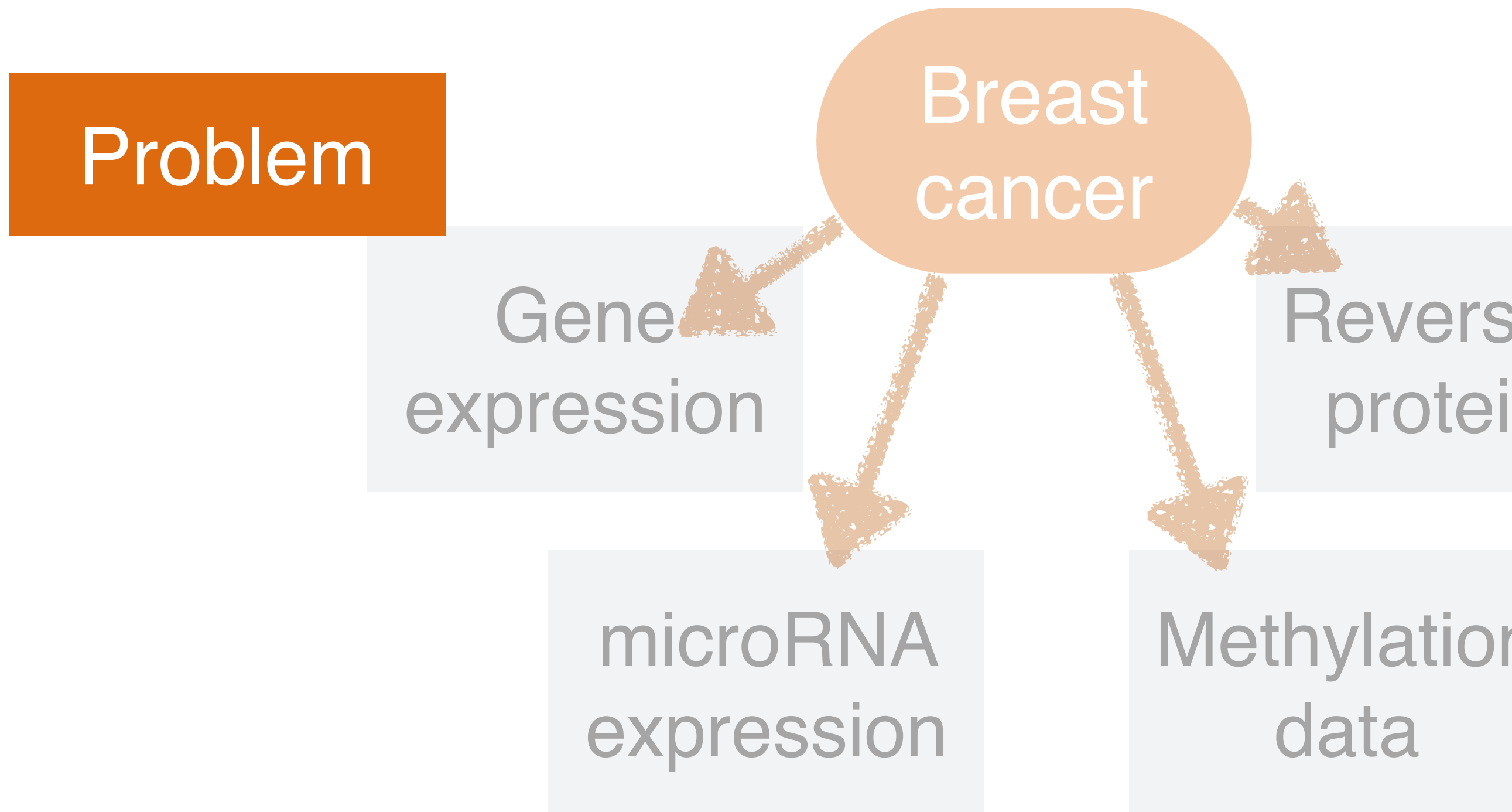
where $X = \max \{x_i; i = 1, \dots, N\}$





```
let logSumExp xs =  
  let maxValue = Array.max xs  
  xs  
  |> Array.map (fun x -> exp(x - maxValue))  
  |> Array.sum  
  |> log  
  |> (+) maxValue
```

Typical workflow

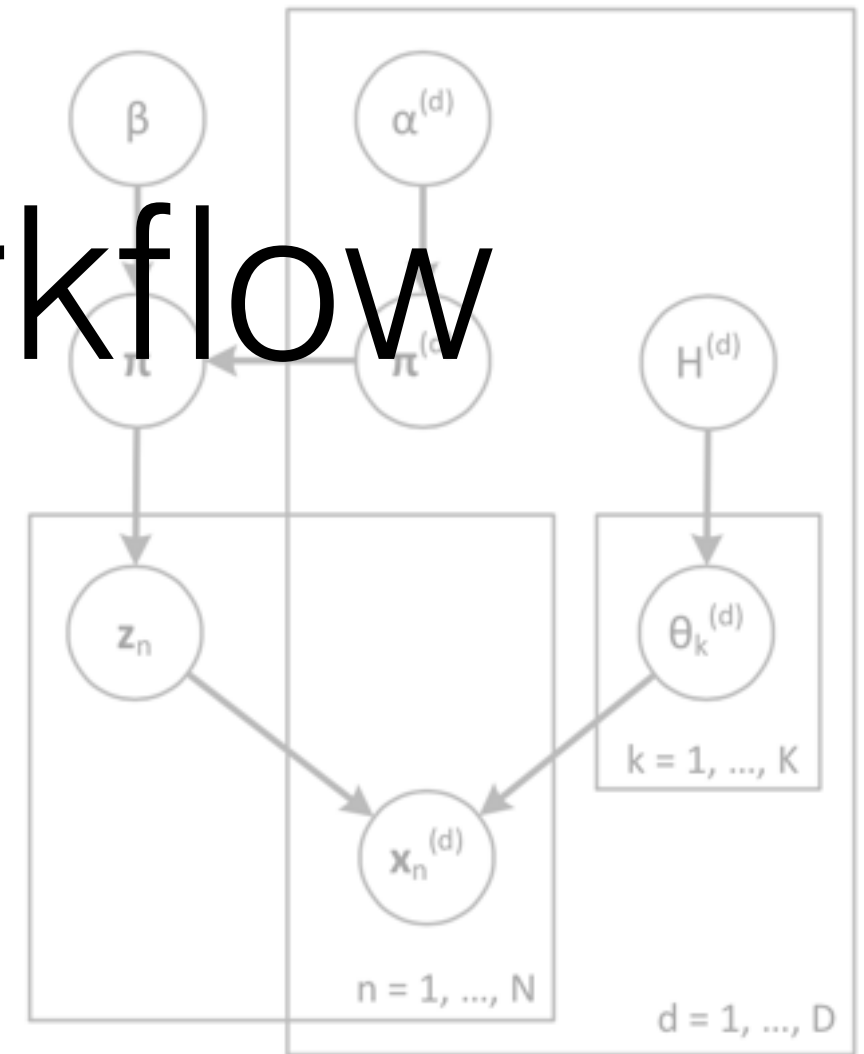


Typical workflow

Problem



Model



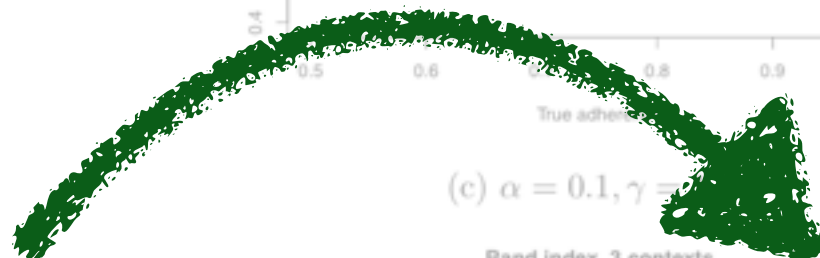
$$\begin{aligned}
 & p(\pi^{(d)} | \alpha_d, \beta, \pi) \\
 & \propto p(\pi^{(d)} | \alpha_d) p(\pi | \pi^{(1)}, \dots, \pi^{(D)}, \beta) \\
 & = \left\{ \frac{\Gamma(K^{(d)} \alpha_d)}{(\Gamma(\alpha_d))^{K^{(d)}}} \prod_{k=1}^{K^{(d)}} (\pi_k^{(d)})^{\alpha_d - 1} \right\} \times \\
 & \quad \times \left\{ \frac{\Gamma(\sum_{i_1=1}^{K^{(1)}} \dots \sum_{i_D=1}^{K^{(D)}} [\beta \times \pi_{i_1}^{(1)} \times \dots \times \pi_{i_D}^{(D)}])}{\prod_{i_1=1}^{K^{(1)}} \dots \prod_{i_D=1}^{K^{(D)}} \Gamma(\beta \times \pi_{i_1}^{(1)} \times \dots \times \pi_{i_D}^{(D)})} \prod_{i_1=1}^{K^{(1)}} \dots \prod_{i_D=1}^{K^{(D)}} (\pi_{i_1, \dots, i_D})^{\beta \pi_{i_1}^{(1)} \dots \pi_{i_D}^{(D)} - 1} \right\} \\
 & \quad \times \frac{\Gamma(\beta)}{\prod_{i_1=1}^{K^{(1)}} \dots \prod_{i_D=1}^{K^{(D)}} \Gamma(\beta \times \pi_{i_1}^{(1)} \times \dots \times \pi_{i_D}^{(D)})} \times \\
 & \quad \times \left\{ \prod_{k=1}^{K^{(d)}} (\pi_k^{(d)})^{\alpha_d - 1} \right\} \left\{ \prod_{i_1=1}^{K^{(1)}} \dots \prod_{i_D=1}^{K^{(D)}} (\pi_{i_1, \dots, i_D})^{\beta \pi_{i_1}^{(1)} \dots \pi_{i_D}^{(D)} - 1} \right\} \\
 & \propto \frac{\Gamma(K^{(d)} \alpha_d)}{(\Gamma(\alpha_d))^{K^{(d)}}} \left\{ \prod_{k=1}^{K^{(d)}} (\pi_k^{(d)})^{\alpha_d - 1} \right\} \left\{ \prod_{i_1=1}^{K^{(1)}} \dots \prod_{i_D=1}^{K^{(D)}} \frac{1}{\Gamma(\beta \times \pi_{i_1}^{(1)} \times \dots \times \pi_{i_D}^{(D)})} (\pi_{i_1, \dots, i_D})^{\beta \pi_{i_1}^{(1)} \dots \pi_{i_D}^{(D)} - 1} \right\}
 \end{aligned}$$

Typical workflow

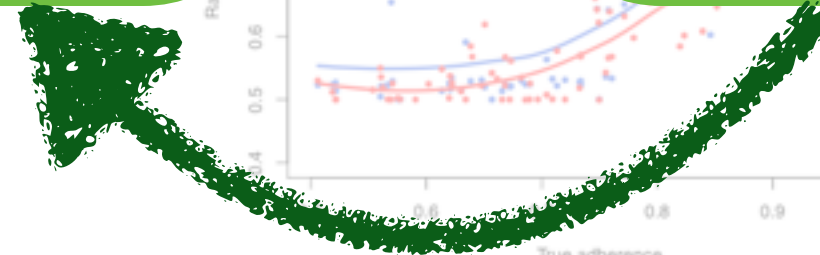
Problem



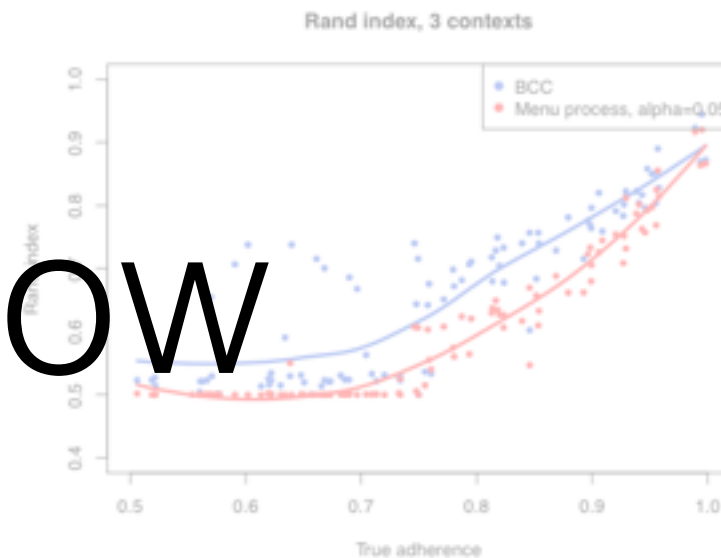
Model



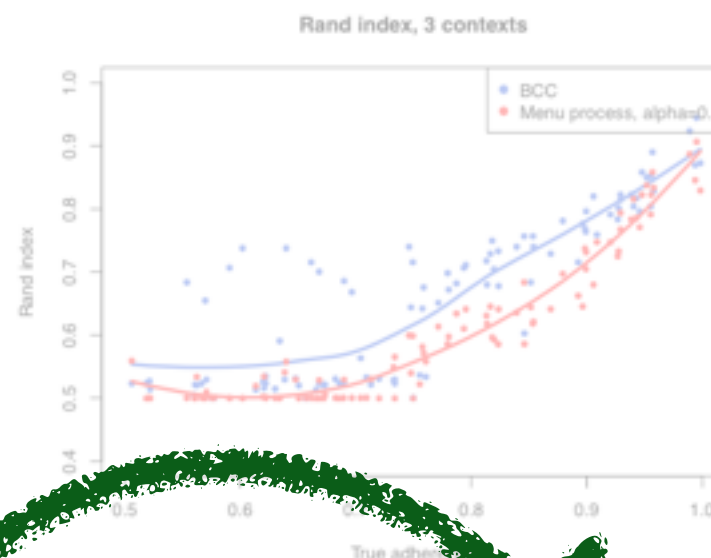
Evaluation



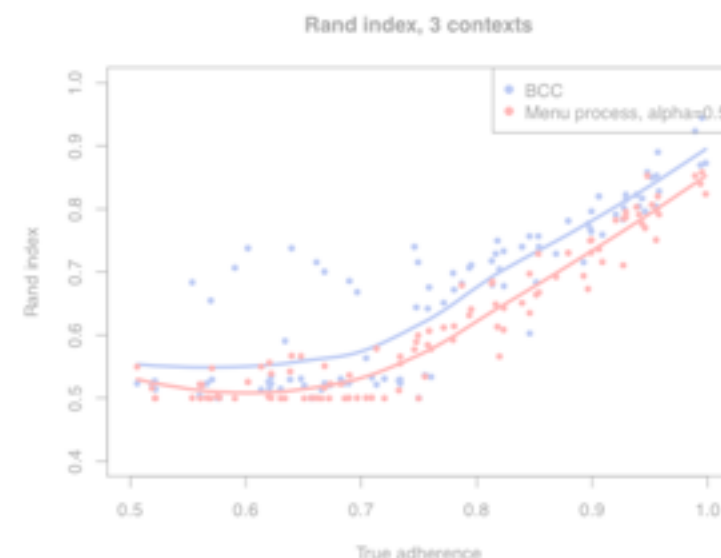
(a) $\alpha = 0.01, \gamma = 0.5$



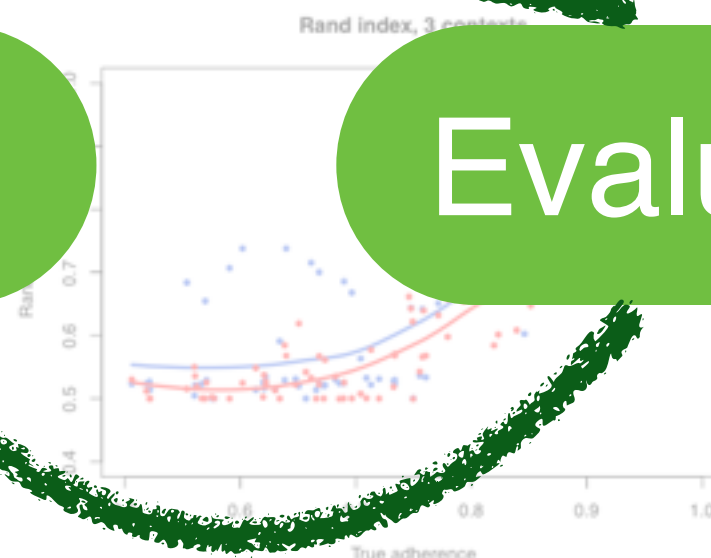
(b) $\alpha = 0.05, \gamma = 0.5$



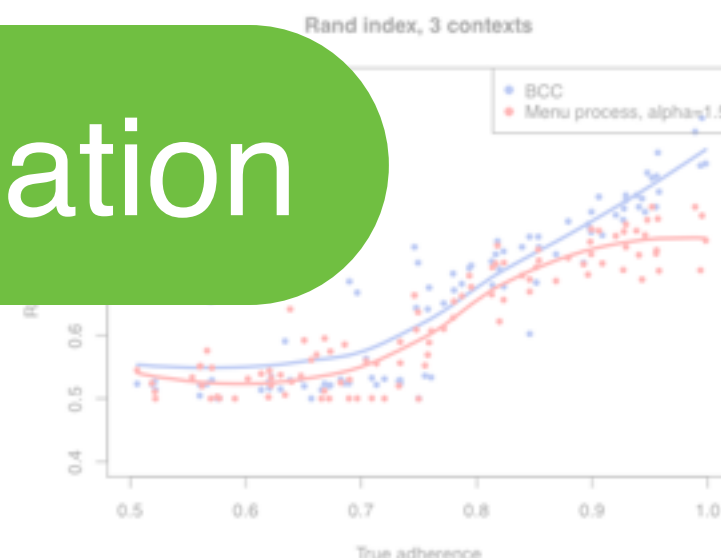
(c) $\alpha = 0.1, \gamma = 0.5$



(d) $\alpha = 0.5, \gamma = 1$

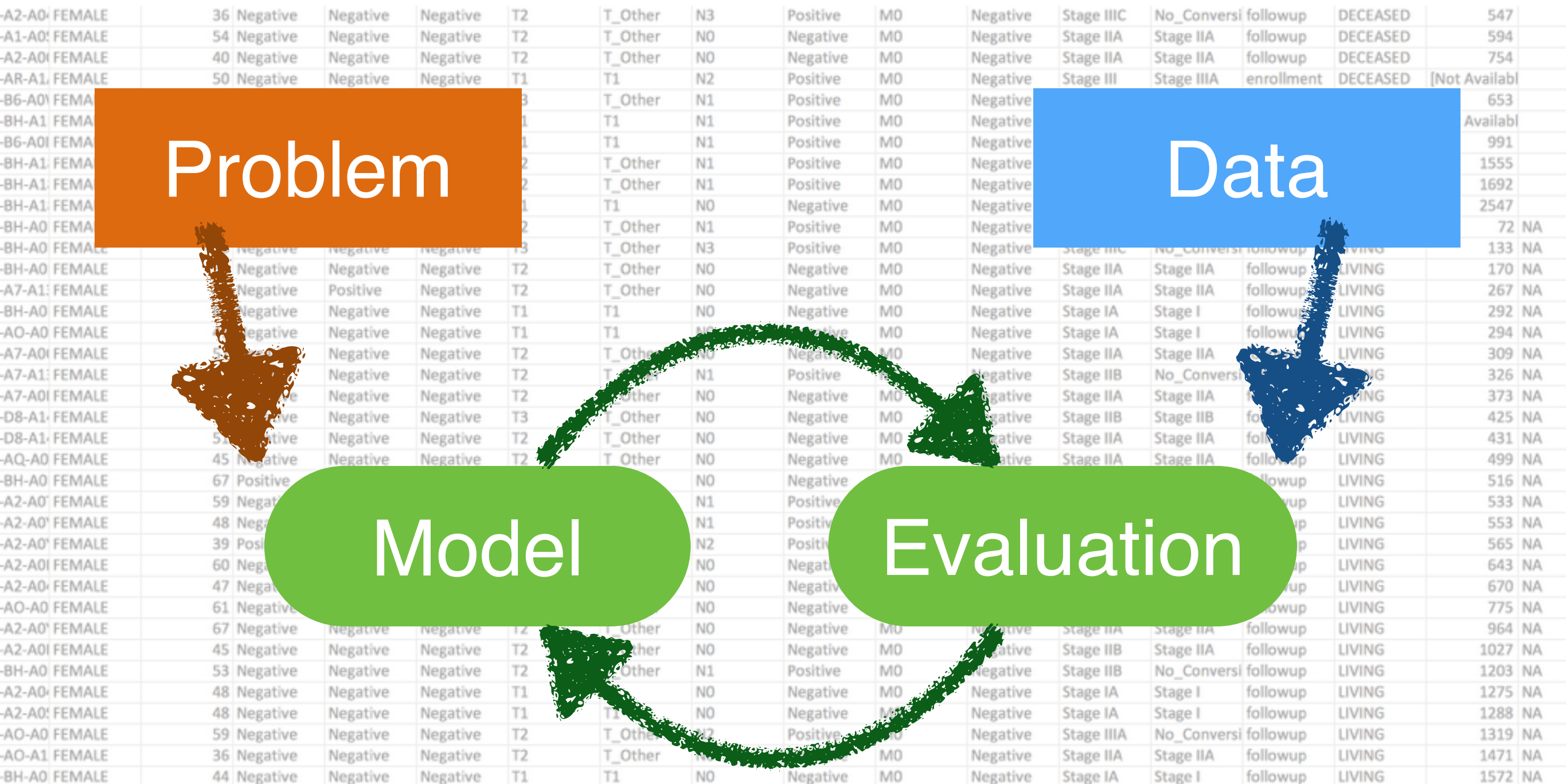


(e) $\alpha = 1, \gamma = 1$

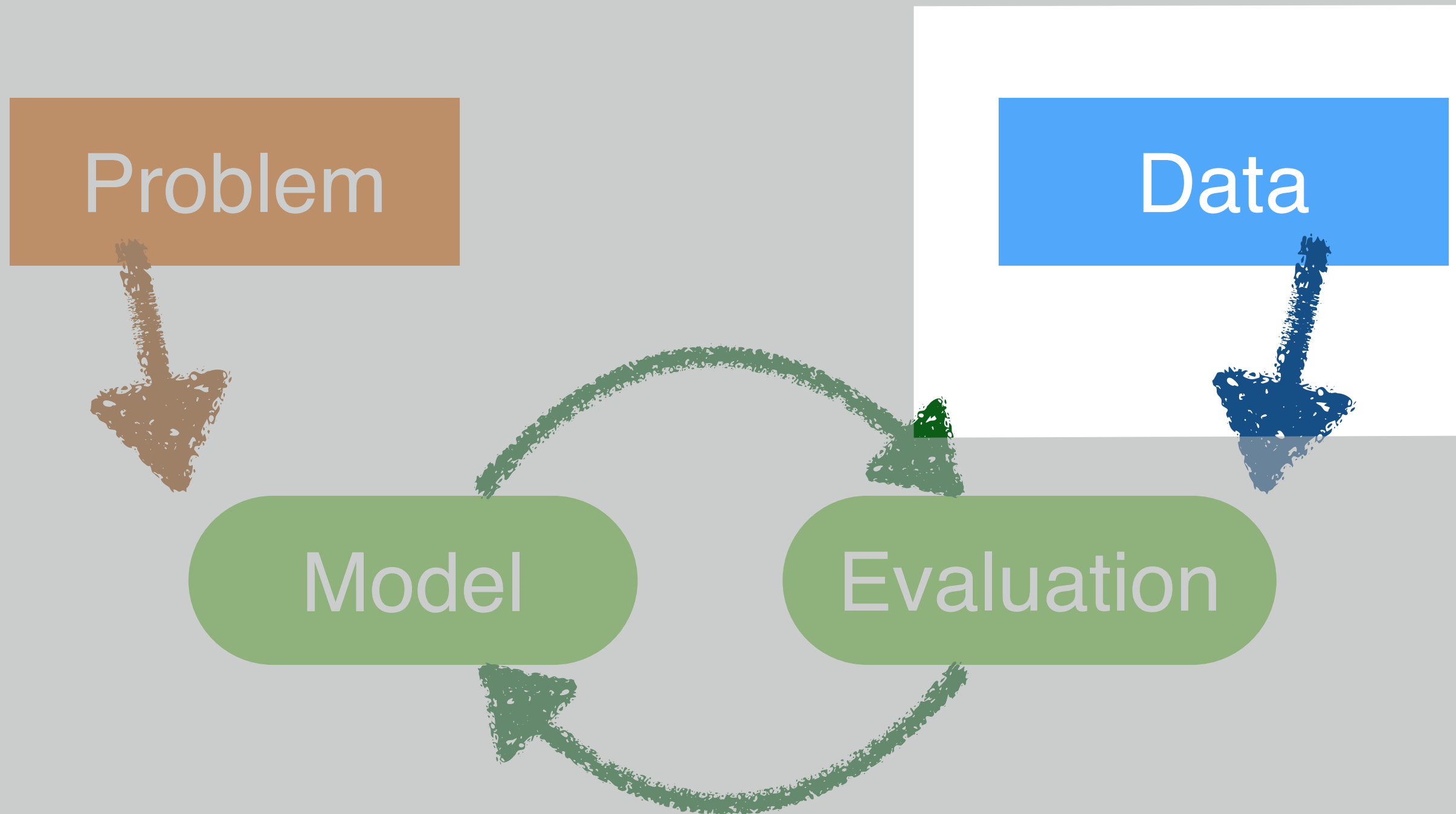


(f) $\alpha = 1.5, \gamma = 1$

Typical workflow

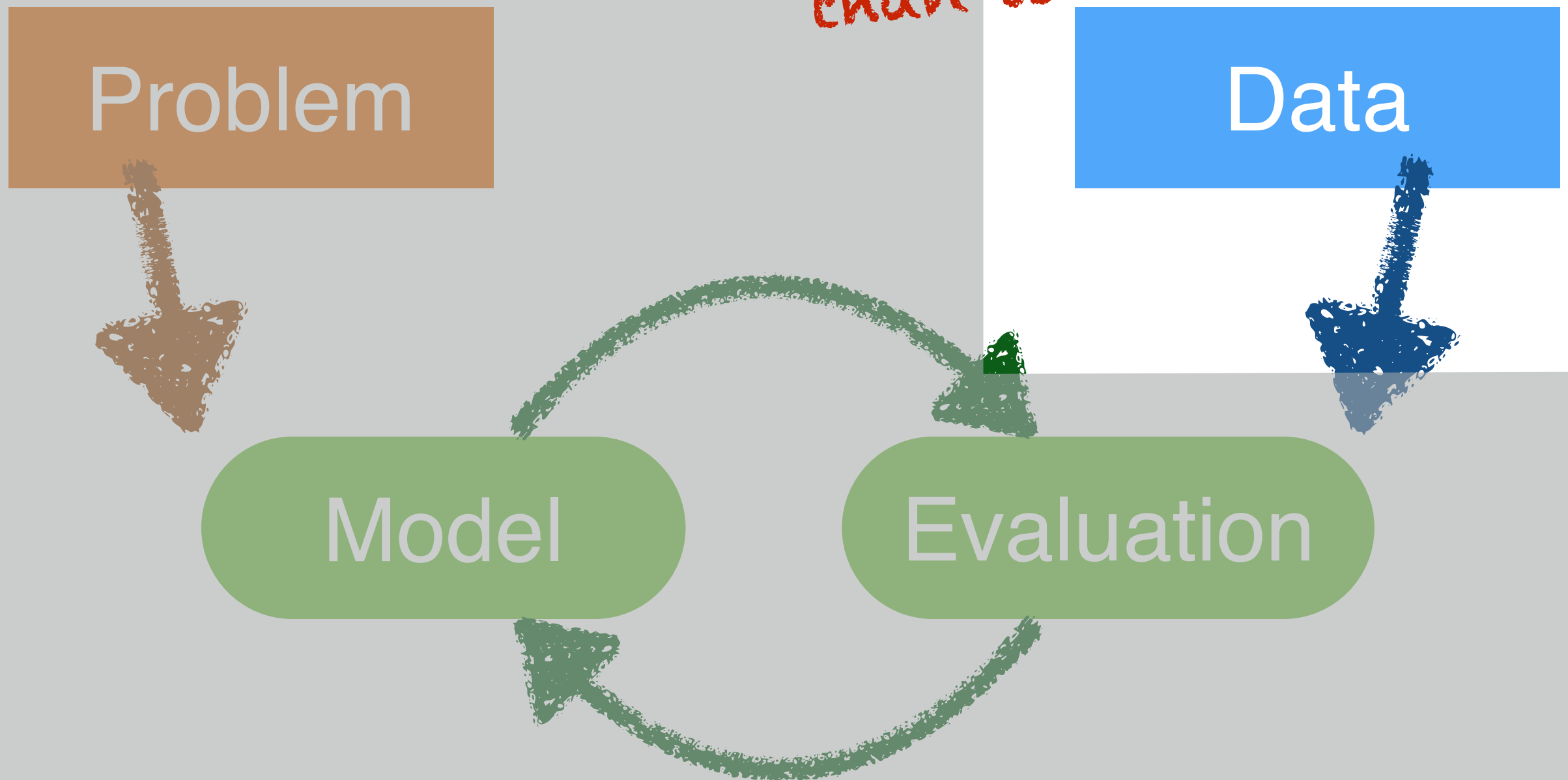


Typical workflow

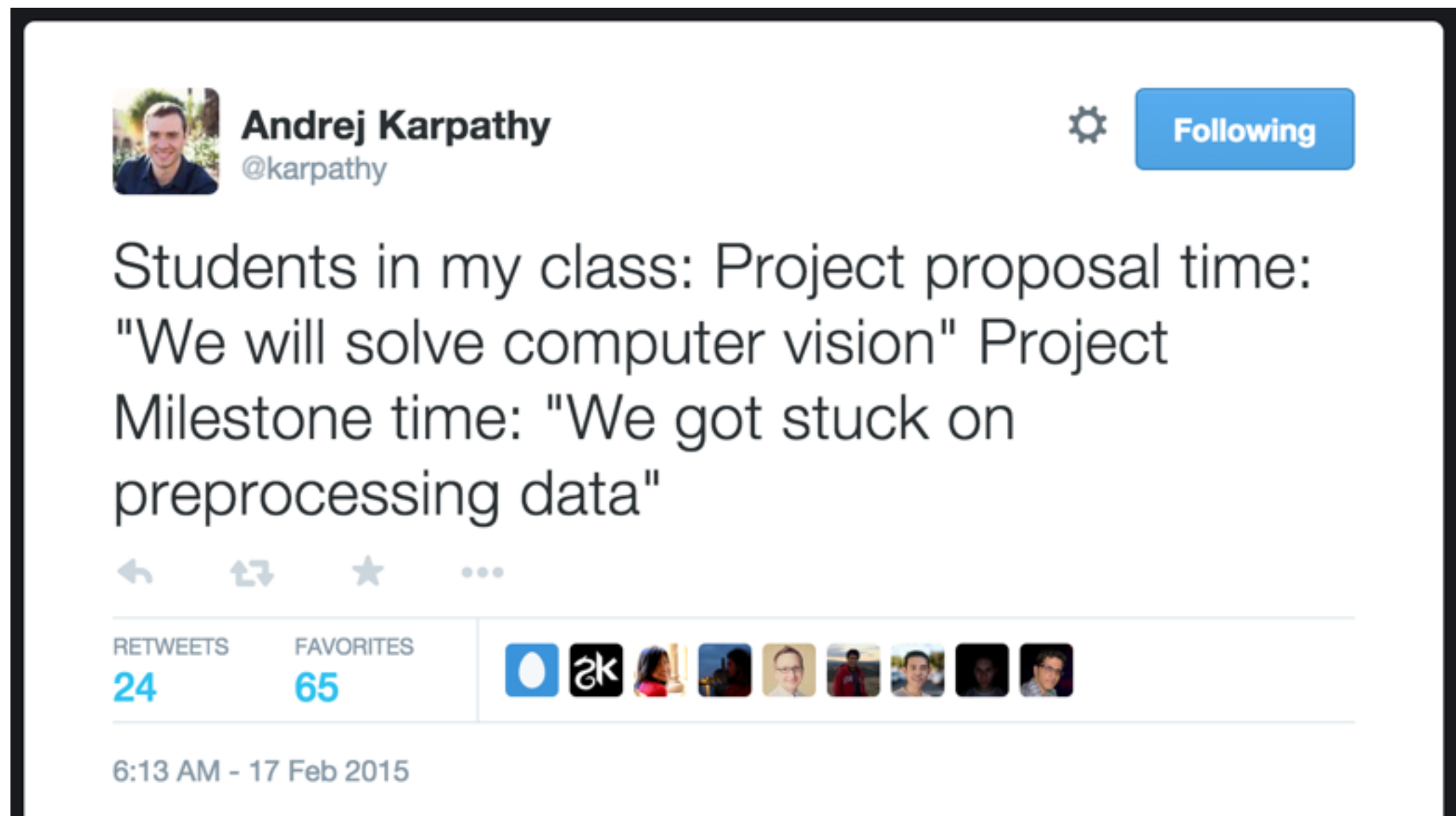


Typical workflow

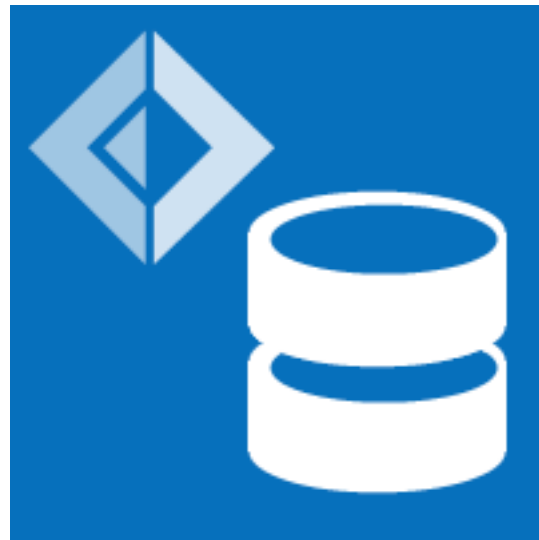
Usually takes much more time
than it should



Dealing with real-world data



Type providers



F# Data - typed access to external data sources

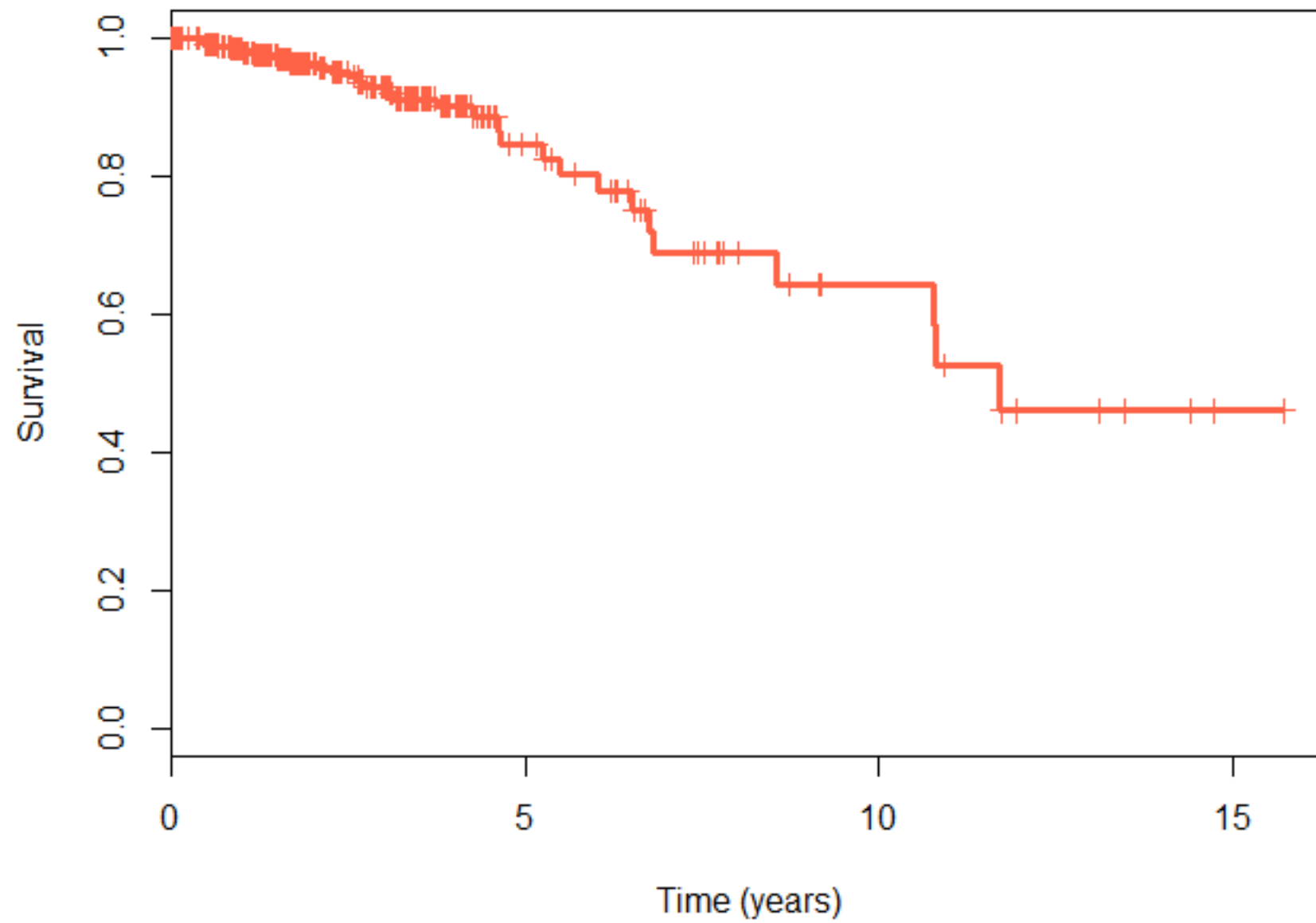
Csv files

JSON, XML, HTML

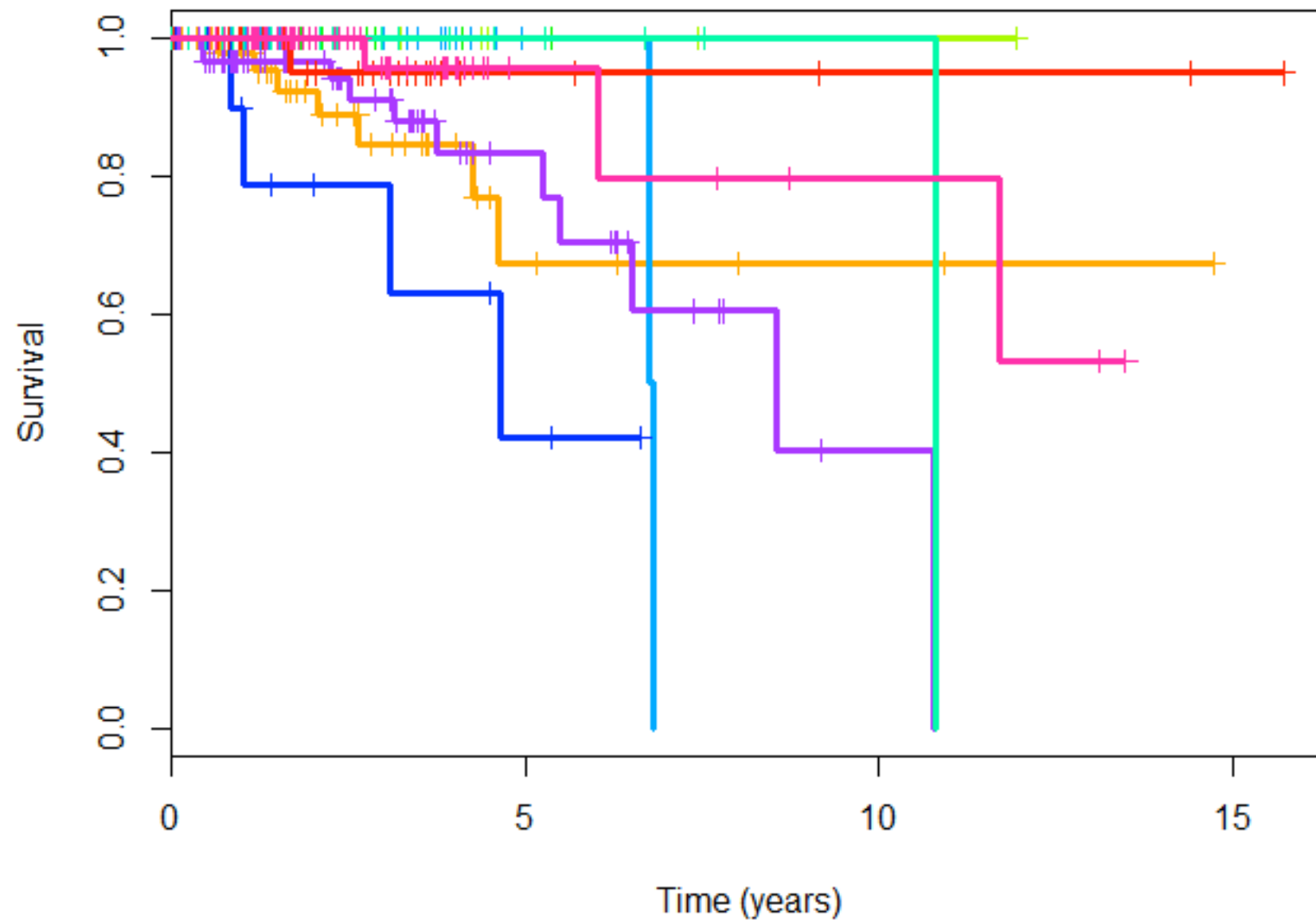
RProvider



Results



Results



Thank you



@evelgab

evelinag.com

evelina@evelinag.com

F# eXchange 17 April in London