

— Nested Effects Models —  
An example in *Drosophila* immune response

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**Abstract**

Cellular signaling pathways, which are not modulated on a transcriptional level, cannot be directly deduced from expression profiling experiments. The situation changes, when external interventions like RNA interference or gene knock-outs come into play.

In Markowetz *et al.* (2005) and Markowetz (2006) we introduced an algorithm to infer non-transcriptional pathway features based on differential gene expression in silencing assays. The method is implemented in the Bioconductor package `nem`. Here we demonstrate its practical use in the context of an RNAi data set investigating the response to microbial challenge in *Drosophila melanogaster*.

We show in detail how the data is pre-processed and discretized, how the pathway can be reconstructed by different approaches, and how the final result can be post-processed to increase interpretability.

## 1 *Drosophila* RNAi data

We applied our method to data from a study on innate immune response in *Drosophila* (Boutros *et al.*, 2002). Selectively removing signaling components blocked induction of all, or only parts, of the transcriptional response to LPS.

**Dataset summary** The dataset consists of 16 Affymetrix-microarrays: 4 replicates of control experiments without LPS and without RNAi (negative controls), 4 replicates of expression profiling after stimulation with LPS but without RNAi (positive controls), and 2 replicates each of expression profiling after applying LPS and silencing one of the four candidate genes *tak*, *key*, *rel*, and *mkk4/hep*.

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**Preprocessing and E-gene selection** For preprocessing, we perform normalization on probe level using a variance stabilizing transformation (Huber *et al.*, 2002), and probe set summarization using a median polish fit of an additive model (Irizarry *et al.*, 2003). The result is included as a dataset in the package `nem`.

```
> library(nem)
> data("BoutrosRNAi2002")
```

The function `nem.discretize` implements the following two preprocessing steps: First, we select the genes as effect reporters (E-genes), which are more than two-fold upregulated by LPS treatment. Next, we transform the continuous expression data to binary values. We set an E-genes state in an RNAi experiment to 1 if its expression value is sufficiently far from the mean of the positive controls, *i.e.* if the intervention interrupted the information flow. If the E-genes expression is close to the mean of positive controls, we set its state to 0.

Let  $C_{ik}$  be the continuous expression level of  $E_i$  in experiment  $k$ . Let  $\mu_i^+$  be the mean of positive controls for  $E_i$ , and  $\mu_i^-$  the mean of negative controls. To derive binary data  $E_{ik}$ , we defined individual cutoffs for every gene  $E_i$  by:

$$E_{ik} = \begin{cases} 1 & \text{if } C_{ik} < \kappa \cdot \mu_i^+ + (1 - \kappa) \cdot \mu_i^-, \\ 0 & \text{else.} \end{cases} \quad (1)$$

```
> res.disc <- nem.discretize(BoutrosRNAiExpression, neg.control = 1:4,
+   pos.control = 5:8, cutoff = 0.7)
```

discretizing with respect to POS and NEG controls

**Estimating error probabilities** From the positive and negative controls, we can estimate the error probabilities  $\alpha$  and  $\beta$ . The type I error  $\alpha$  is the number of positive controls discretized to state 1, and the type II error  $\beta$  is the number of negative controls in state 0. To guard against unrealistically low estimates we add pseudo counts. The error estimates are included into the discretization results:

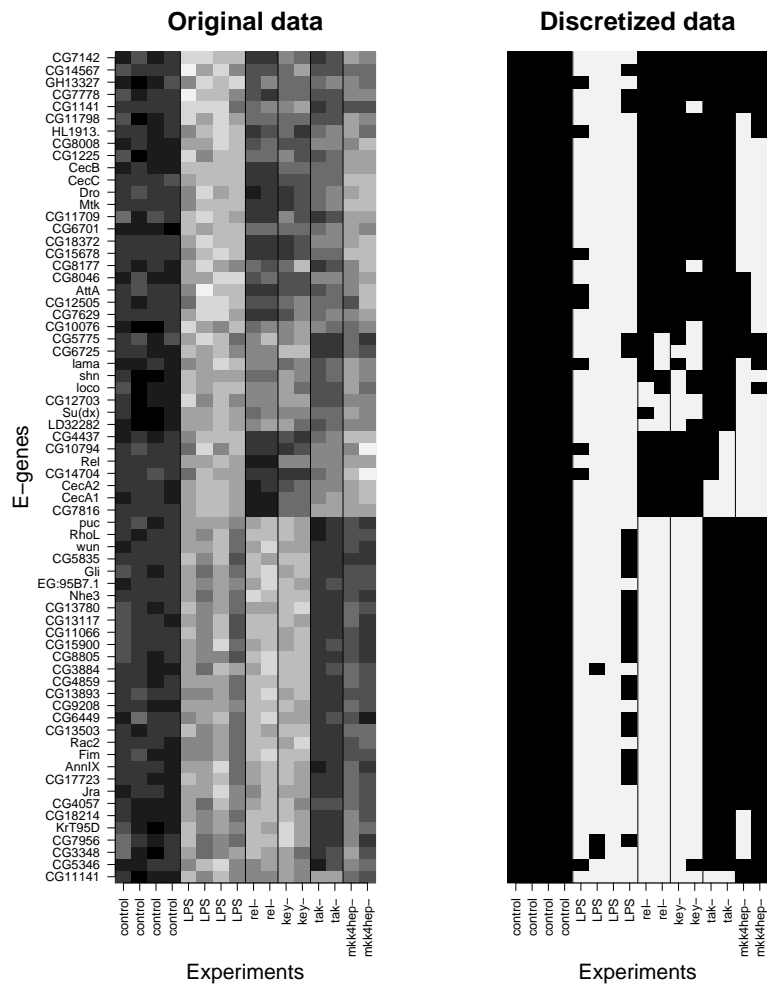


Figure 1: Continuous and discretized data

## 2 Applying Nested Effects Models

Which model explains the data best? With only four S-genes, we can exhaustively enumerate all pathway models and search the whole space for the best-fitting model. To score these models use either the marginal likelihood depending on  $\alpha$  and  $\beta$  (details found in Markowitz et al (2005)) or the full marginal likelihood depending on hyperparameters (details in Markowitz, 2006). Additionally we show how to employ an edge-wise inference heuristic, which can also be applied to cases where exhaustive search over model space is infeasible (i.e. when we have more than 4 or 5 perturbed genes). An interface to all inference techniques is provided by the function `nem()`.

### 2.1 Exhaustive search by marginal likelihood

Scoring models by marginal log-likelihood is implemented in function `score`. Input consists of models and data, the type of the score ("mLL" or "FULLmLL"), the corresponding parameters (`para`) or hyperparameters (`hyperpara`) and a prior for E-gene positions (`P`).

```
> result <- nem(res.disc$dat, type = "mLL", para = res.disc$para,  
+ inference = "search")
```

```
Generated 355 unique models ( out of 4096 )  
Computing marginal likelihood for 355 models
```

```
> result
```

```
Object of class 'score' generated by 'score()'
```

```
$graph: phenotypic hierarchy on genes  
$mLL:   a vector of length 355  
$pos:   a list   of length 355  
$mappos: a vector of length 355  
$lambda: 0
```

The output is the highest scoring model (`result$graph`), a vector of scores (`result$mLL`) and a list of E-gene position posteriors (`result$pos`), and a MAP estimate of E-gene positions (`result$mappos`). We can plot the results using the commands:

```
> plot(result, what = "graph")  
> plot(result, what = "mLL")  
> plot(result, what = "pos")
```

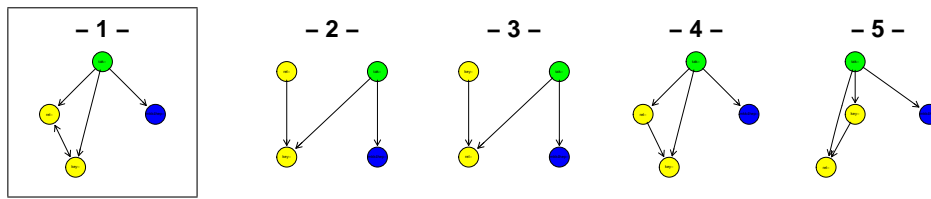


Figure 2: The five silencing schemes getting high scores in Fig. ???. It takes a second to see it, but Nr.2 to 5 are not that different from Nr.1. The main feature, ie. the branching downstream of *tak* is conserved in all of them.

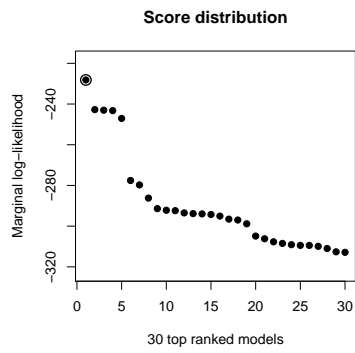


Figure 3: The best 30 scores

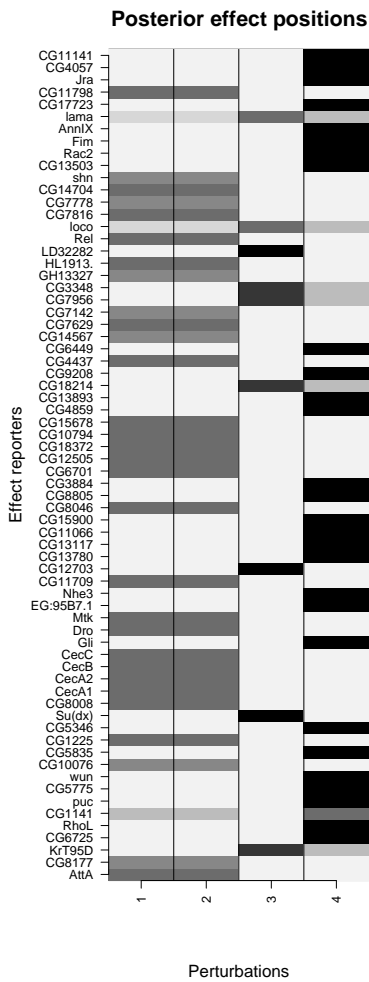


Figure 4: Posterior distributions of E-gene positions given the highest scoring silencing scheme (Nr. 1 in Fig. 2). The MAP estimate corresponds to the row-wise maximum.

## 2.2 Exhaustive search Full marginal likelihood

Additionally to what we did in the paper (Markowitz *et al.*, 2005) the PhD thesis (Markowitz, 2006) contains equations for a “full marginal likelihood” in which error probabilities  $\alpha$  and  $\beta$  are integrated out. This section shows that using this score we learn the same pathways as before.

```
> result2 <- nem(res.disc$dat, type = "FULLmLL", hyperpara = c(1,  
+ 9, 9, 1), inference = "search")
```

```
Generated 355 unique models ( out of 4096 )  
Computing FULL marginal likelihood for 355 models
```

```
> result2
```

```
Object of class 'score' generated by 'score()'
```

```
$graph: phenotypic hierarchy on genes  
$mLL: a vector of length 355  
$pos: a list of length 355  
$mappos: a vector of length 355  
$lambda: 0
```

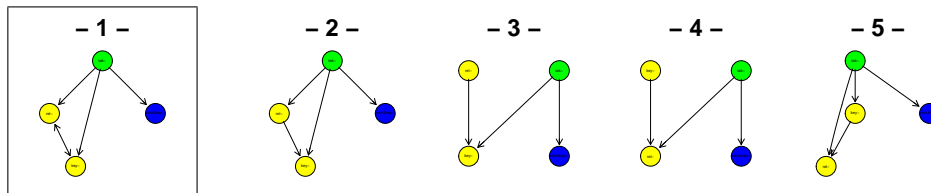


Figure 5: Same topologies as before.

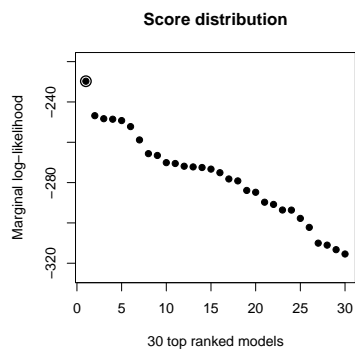


Figure 6: The best 30 scores by full marginal likelihood



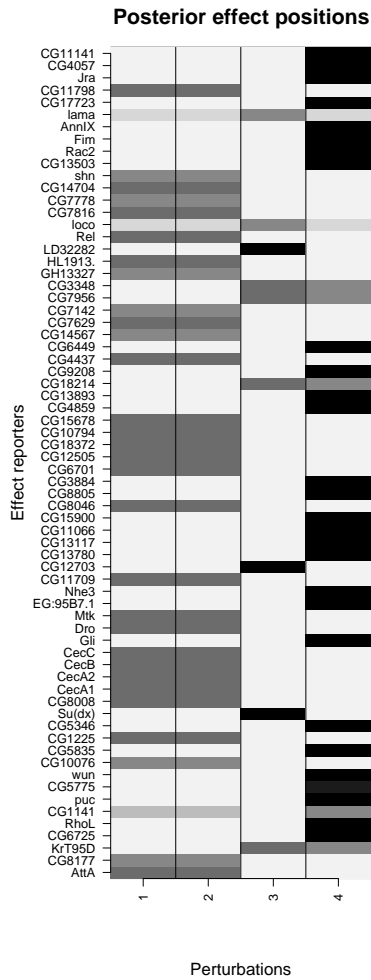


Figure 7: Posterior distributions of E-gene positions given the highest scoring silencing scheme (Nr. 1 in Fig. 5). The MAP estimate corresponds to the row-wise maximum.

## 2.3 Edge-wise learning

Instead of scoring whole pathways, we can learn the model edge by edge. For each pair of genes  $A$  and  $B$  we infer the best of four possible models:  $A \cdot B$  (unconnected),  $A \rightarrow B$  (effects of  $A$  are superset of effects of  $B$ ),  $A \leftarrow B$  (subset), and  $A \leftrightarrow B$  (undistinguishable effects).

```
> result3 <- nem(res.disc$dat, para = res.disc$para, inference = "pairwise")
```

```
4 perturbed genes -> 6 pairwise tests (lambda = 0 )
```

```
.....
```

```
estimating effect positions
```

```
> result3
```

```
Object of class 'pairwise' generated by 'pairwise.posterior()'
```

```
$graph: phenotypic hierarchy on genes)
```

```
$scores: posterior distributions of local models
```

```
Summary of MAP estimates:
```

```
all .. -> <->
  6  2  3  1
```

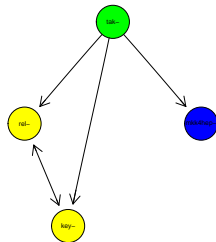


Figure 8: Result of edge-wise learning. Compare this to the result from global search. It looks exactly the same.

## 2.4 Inference from triples

Edge-wise learning assumes independence of edges. But this is not true in transitively closed graphs, where a direct edge must exist whenever there is a longer path between two nodes. Natural extension of edge-wise learning is inference from triples of nodes. In the package `nem` we do it by

```
> result4 <- nem(res.disc$dat, para = res.disc$para, inference = "triples")  
> result4
```

### 3 Visualization

```
> plot.effects(res.disc$dat, result)
```

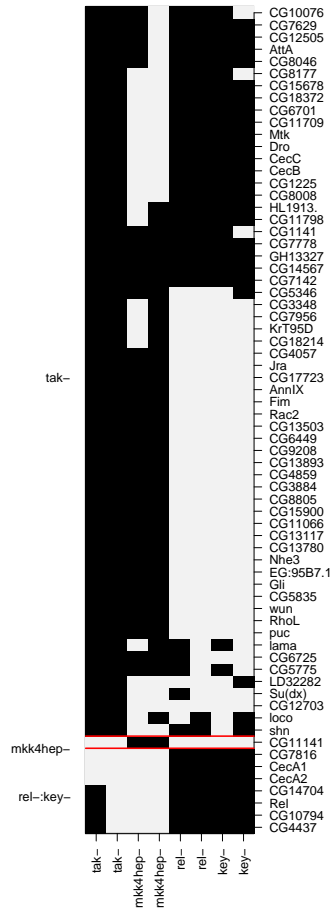


Figure 9: plotting data according to inferred hierarchy

## 4 Post-processing of results

**Combining strongly connected components** First, we identify all nodes/genes which are not distinguishable given the data. This amounts to finding the strongly connected components in the graph. Relish and Key are now combined into one node.

```
> result3.scc <- SCCgraph(result3$graph, name = TRUE)
> plot(result3.scc$graph)
```

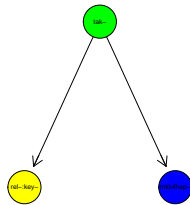


Figure 10: The undistinguishable profiles of *key* and *rel* are summarized into a single node.

**Transitive reduction** Additionally, in bigger graphs `transitive.reduction()` helps to see the structure of the network better. In this simple example there are no shortcuts to remove.

## References

- [Boutros *et al.* (2002)] Boutros M, Agaisse H, Perrimon N. Sequential activation of signaling pathways during innate immune responses in *Drosophila*. *Developmental Cell*, 3(5):711–722, 2002.
- [Huber *et al.* (2002)] Huber W, Heydebreck A, Sültmann H, Poustka A, Vingron M. Variance Stabilization Applied to Microarray Data Calibration and to the Quantification of Differential Expression. *Bioinformatics*, 18:S96–S104, 2002.
- [Irizarry *et al.* (2003)] Irizarry RA, Bolstad BM, Collin F, Cope LM, Hobbs B, Speed TP. Summaries of Affymetrix GeneChip probe level data. *Nucleic Acids Res.* 31(4):e15, 2003.
- [Markowetz *et al.* (2005)] Markowetz F, Bloch J, Spang R. Non-transcriptional pathway features reconstructed from secondary effects of RNA interference *Bioinformatics*, 2005
- [Markowetz (2006)] Markowetz F. Probabilistic Models for Gene Silencing Data. *PhD thesis*, Free University Berlin, 2005

## Session Information

The version number of R and packages loaded for generating the vignette were:

- R version 2.5.0 (2007-04-23), x86\_64-unknown-linux-gnu
- Locale: LC\_CTYPE=en\_US;LC\_NUMERIC=C;LC\_TIME=en\_US;LC\_COLLATE=en\_US;LC\_MONETARY=en\_US
- Base packages: base, datasets, graphics, grDevices, methods, stats, tools, utils
- Other packages: annotate 1.14.1, Biobase 1.14.0, class 7.2-33, e1071 1.5-16, genefilter 1.14.0, graph 1.14.0, lattice 0.15-4, nem 1.6.0, RBGL 1.12.0, Rgraphviz 1.14.0, time 1.0