

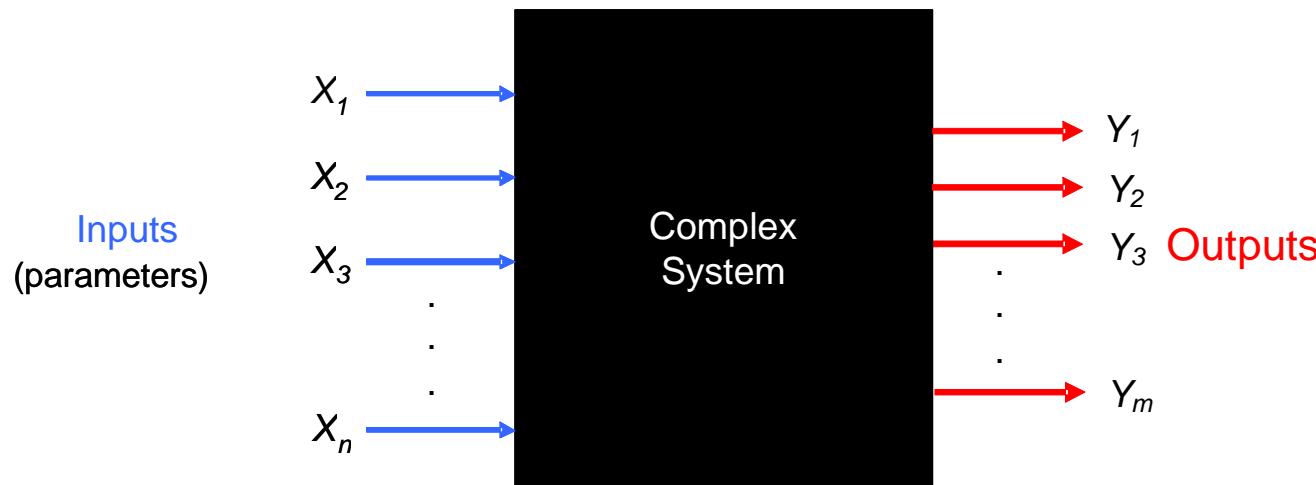
# AN INFORMATION-THEORETIC FRAMEWORK FOR GLOBAL SENSITIVITY ANALYSIS

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# Parameter Sensitivity Analysis

- Pathway model as ‘black box’:



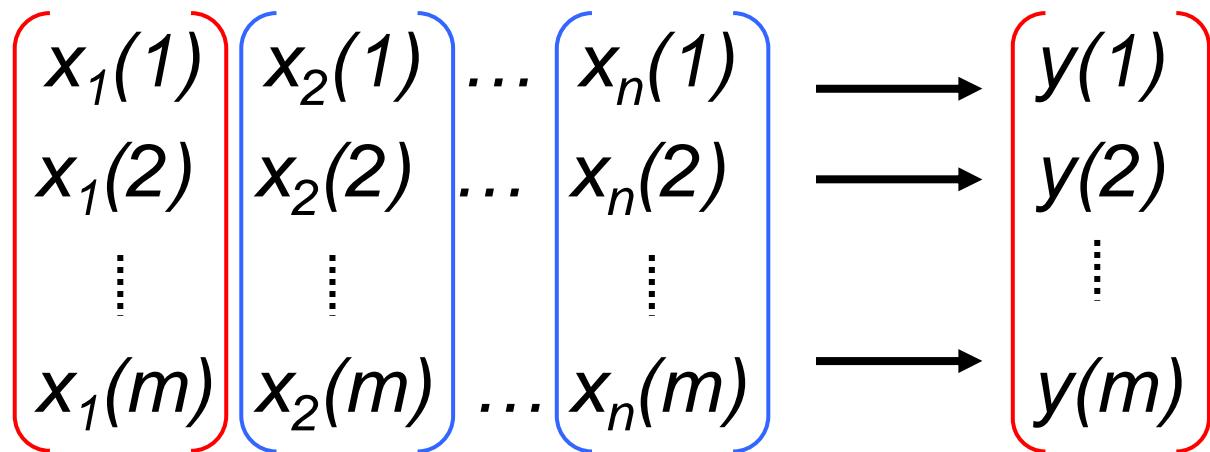
- Input-output mapping not explicit (e.g. ODE system)
- Which parameters are important?
- Do they interact?

# Global Sensitivity Analysis

- Perturbing *all* inputs/parameters simultaneously => **randomisation**
- Inputs and outputs become random variables with pdfs  $p(x_i)$  and  $p(y)$ .

# Defining Sensitivity

- Result of repeated simulation:



- Sensitivity defined in terms of *associations* between sequences of random values (*columns*).

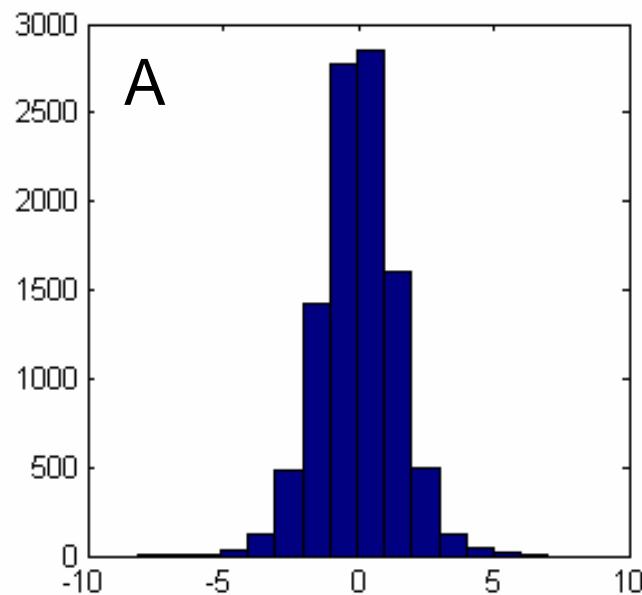
# Information Theory

- Relates **uncertainty** and **association** ('correlation'):
  - Random parameter sampling creates output uncertainty, measured by **entropy**  $H(Y)$
  - Input-output associations measured by **mutual information**  $I(X;Y)$
- Complex system as a '**communication channel**'.  
*How much information does  $X_i$  provide about Y?*

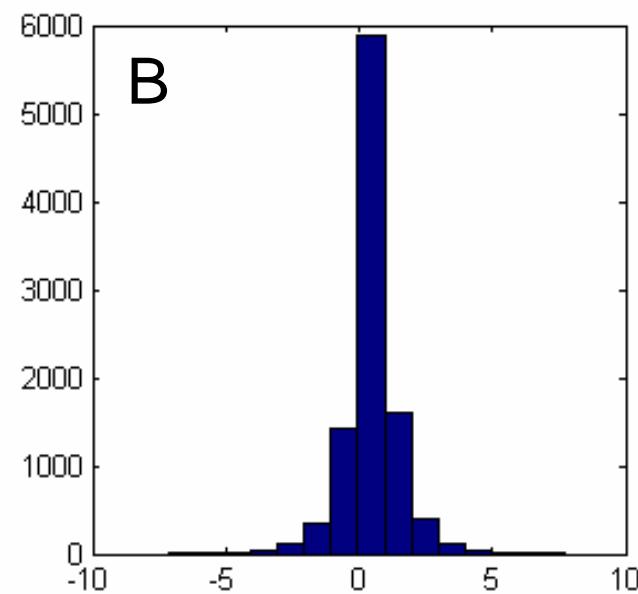
Answer:  $I(X_i;Y) = H(Y) - H(Y | X_i).$

Example:  $y = x_1 * x_2 + x_3$  ( $x_1, x_2, x_3$  normally distributed)

Unconditional output histogram



Output histogram for **fixed**  $x_3 = 0.5$



- Conditioning (fixing parameters) reduces output entropy (uncertainty):  $H(Y|X_i) \leq H(Y)$

# First-order Sensitivity

- Normalised mutual information (Crutchfield et al. 1986)

$$s_i = \frac{I(X_i; Y)}{H(Y)},$$

where we choose to *discretise* variables:

$$\begin{aligned} H(Y) &= -\sum_y p(y) \log_2 p(y) \\ I(X_i; Y) &= \sum_{x_i} \sum_y p(x_i, y) \log_2 \frac{p(x_i, y)}{p(x_i) p(y)}. \end{aligned}$$

# Second-order Interactions

- Captured by the **conditional mutual information**

$$I(X_i; X_j | Y) = \sum_F p(y) \sum_{k_i, k_j} p(x_i, x_j | y) \log_2 \frac{p(x_i, x_j | y)}{p(x_i | y) p(x_j | y)}$$

Requirement: parameters sampled independently

General form:

$$\underbrace{I(\{X_i, X_j\}; Y)}_{\text{1st+2nd-order}} - \underbrace{I(X_i; Y) + I(X_j; Y)}_{\text{1st-order}} = \underbrace{I(X_i; X_j | Y) - \underbrace{I(X_i, X_j)}_{\text{input 'correlation'}}}_{\text{2nd-order}}.$$

# Third-order Interactions

- Decomposition for 3 independent variables yields:

$$\begin{aligned} I(\{X_1, X_2, X_3\}; Y) &= \underbrace{I(X_1; Y) + I(X_2; Y) + I(X_3; Y)}_{1st-order} \\ &\quad + \underbrace{I(X_1; X_2 | Y) + I(X_1; X_3 | Y) + I(X_2; X_3 | Y)}_{2nd-order} \\ &\quad + \underbrace{I(X_2; X_3 | X_1, Y) - I(X_2; X_3 | Y)}_{3rd-order}. \end{aligned}$$

- We define as third-order measure:

$$I_3(X_1; X_2; X_3 | Y) \stackrel{\text{def}}{=} I(X_2; X_3 | X_1, Y) - I(X_2; X_3 | Y).$$

# Conditional ‘Interaction Information’

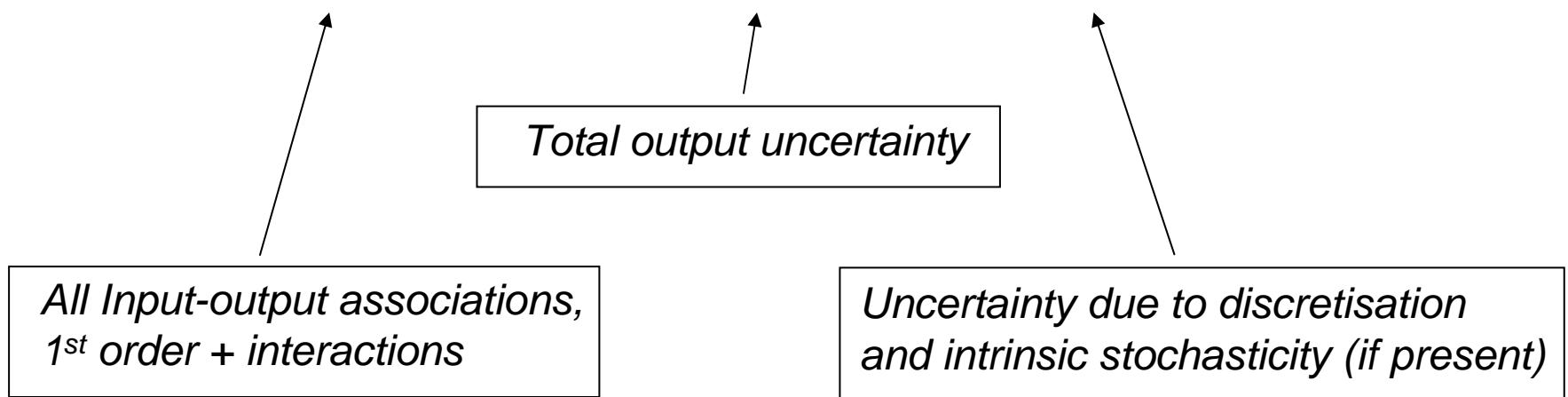
$$I_3(X_1; X_2; X_3 | Y) \stackrel{\text{def}}{=} I(X_2; X_3 | X_1, Y) - I(X_2; X_3 | Y).$$

- Unconditional form introduced by McGill (1954)
- Captures genuine 3-way interaction
- Symmetrical in  $X_i$
- Non-negative except for systems with extreme antisymmetry (*very rare*)

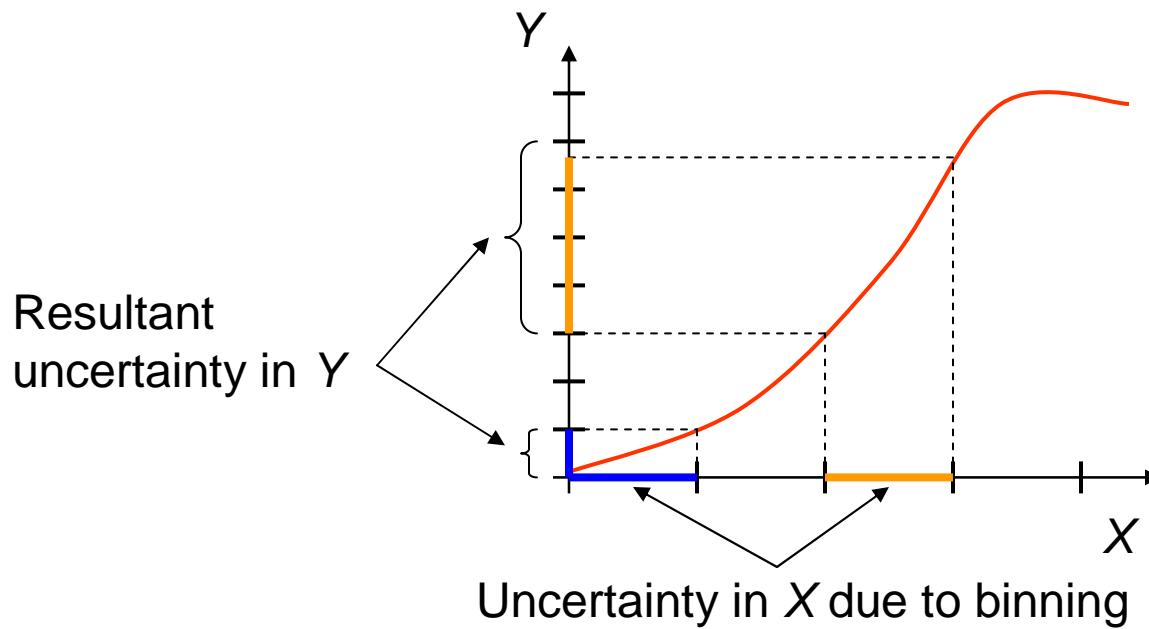
# General Information Balance

- $n$  parameters  $X_1, \dots, X_n$  and one output  $Y$ :

$$I(\{X_1, \dots, X_n\}; Y) = H(Y) - H(Y | X_1, \dots, X_n)$$



# Discretisation Effects



- If all parameters are known with *finite* precision, there can still be a *residual uncertainty* in  $Y$ , the *discretisation entropy*:

$$H_{\Delta} = H(Y | X_1, \dots, X_n) \geq 0$$

# Information Decomposition

$$I(X_1, \dots, X_n; Y) = H(Y) - H(Y | X_1, \dots, X_n)$$



- Total information can be written as sum of all information-theoretic sensitivity measures:

$$\begin{aligned} I(X_1, \dots, X_n; Y) &= \sum_{i=1}^n I(X_i; Y) + \sum_{i < j} I(X_i; X_j | Y) + \sum_{i < j < l} I_3(X_i; X_j; X_l | Y) + \dots \\ &= H(Y) - H(Y | X_1, \dots, X_n) \end{aligned}$$

# General Summation Theorem

$$\frac{1}{H(Y) - H_{\Delta}} \left\{ \sum_{i=1}^n I(X_i; Y) + \sum_{\substack{i,j=1 \\ i < j}}^n \left[ I(X_i; X_j | Y) - I(X_i; X_j) \right] + \right. \\ \left. + \sum_{\substack{i,j,k=1 \\ i < j < k}}^n \left[ I_3(X_i; X_j; X_k | Y) - I_3(X_i; X_j; X_k) \right] + \dots \right\} = 1$$

- Correction terms account for input correlations.  
*con:* more computation time.  
*pro:* greater flexibility for sampling; higher orders?

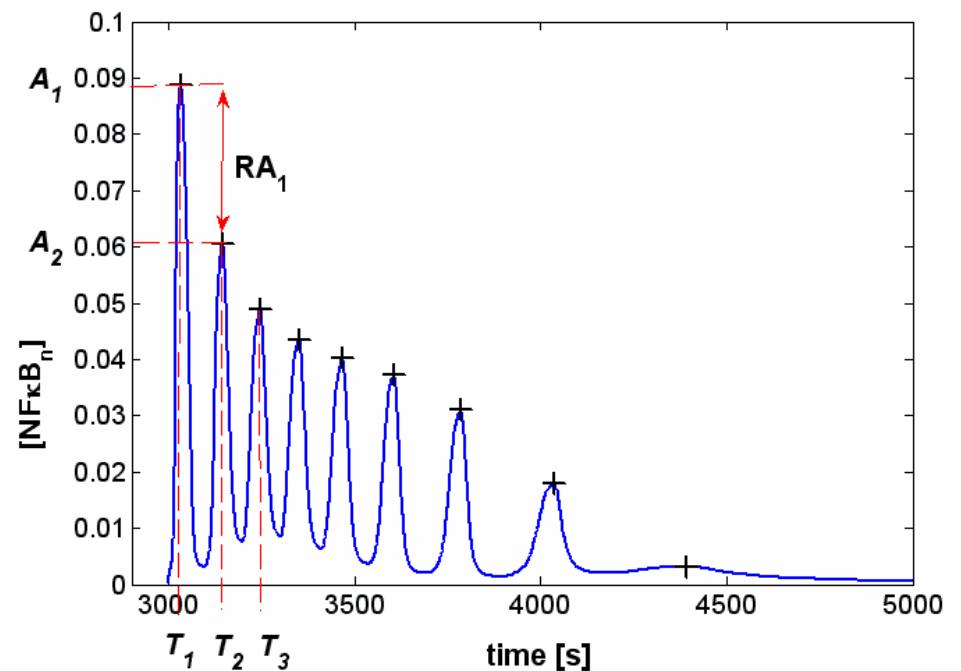
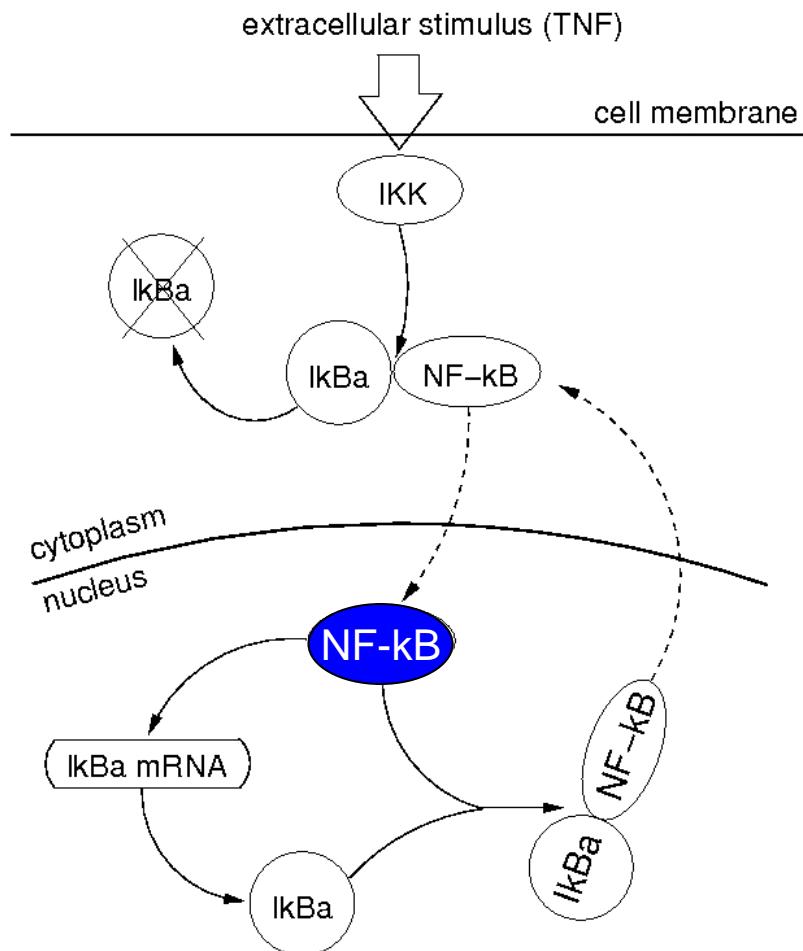
# The Total Sensitivity Index

- Originally defined in variance-based method
- Captures the fraction of variance removed by a particular parameter and *all* its interactions.
- Information-theoretic equivalent:

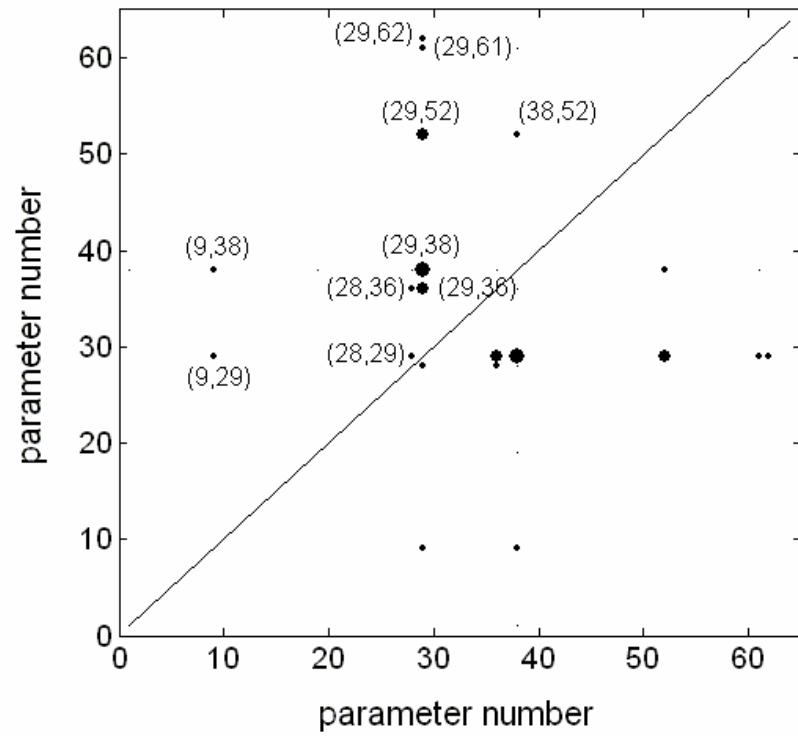
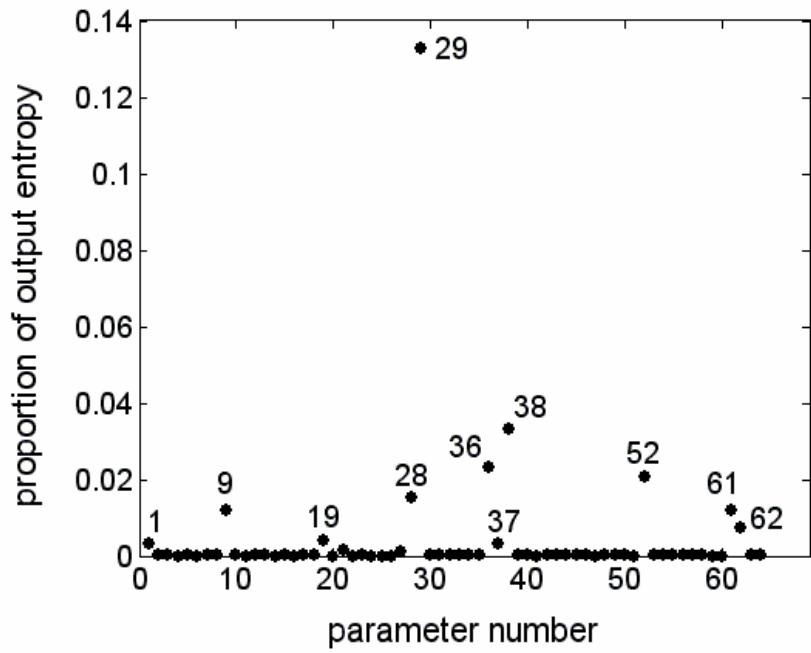
$$S_{total, i} = \frac{H(Y | \{X_1, \dots, X_n\} \setminus X_i)}{H(Y) - H_\Delta}$$

- Equals sum of all sensitivity indices containing parameter  $X_i$  but is calculated via Monte Carlo.

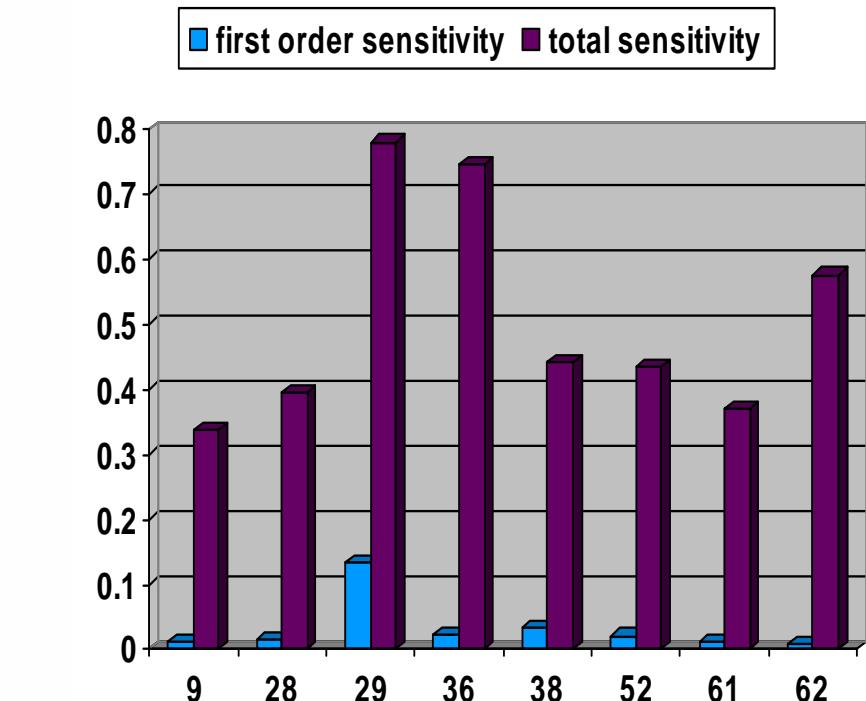
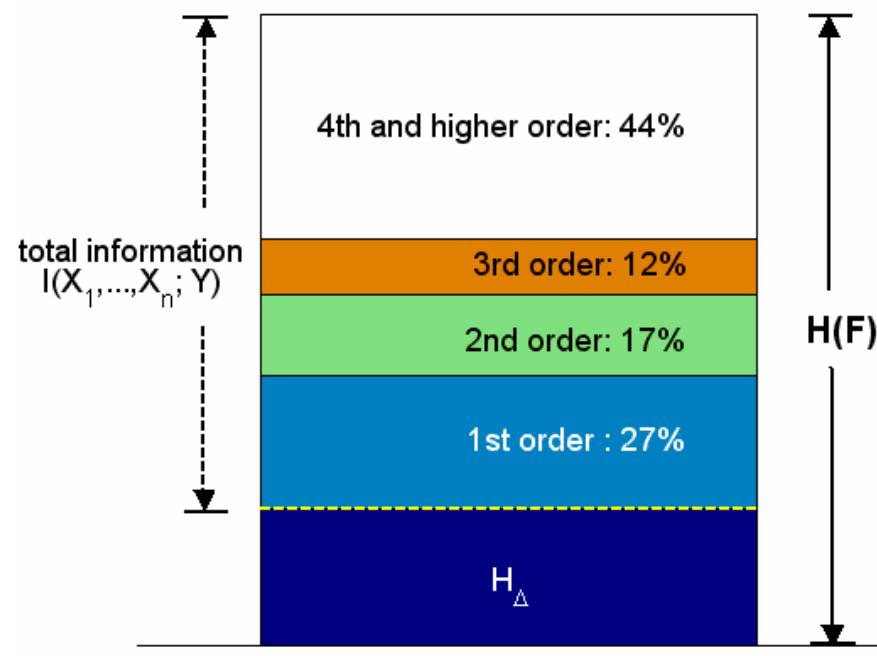
# Example: (I $\kappa$ B)NF- $\kappa$ B pathway



# First and Second Order



# Visualisation of Sensitivity Analysis



- Interactions are very prominent
- 4<sup>th</sup> and higher-order interactions contribute significantly!

# Conclusions

- Novel framework for global sensitivity analysis based on information theory
- Systems Biology: reveals parameter interactions in complex non-linear system (NF- $\kappa$ B pathway)
- Method can incorporate correlated inputs
- Applicable to deterministic and stochastic systems
- Publication: Ludtke et al. (2007), **Information-theoretic Sensitivity Analysis: a general method for credit assignment in complex networks** *J. Royal Soc. Interface*, in print
- Email [Niklas.Ludtke@manchester.ac.uk](mailto:Niklas.Ludtke@manchester.ac.uk) for preprints

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