On the relation between gene organization, functional gene groups and cancer

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Background

Until early 2000s

- Gene order in eukarayotes was believed to be random
- Relatively little was known about gene functionality
- Limited data about chromosomal location of genes

What changed?

- Availability of data
- Gene expression
- Whole-genome sequences
- Gene functionality

Previous Studies

Main findings for non-random gene order

- Genes from the same metabolic **pathway** tend to cluster (e.g. J.M. Lee, E.L. Sonnhammer 2003)
- Genes with similar and/or coordinated **expression** tend to cluster (e.g. Cho et al. 2005)
- Adjacent genes are often co-regulated by the same transcription factor (Hershberg et al. 2005)

Methods

Pathways - Proximity of genes within each pathway.

Expression - Correlation between genes within a sliding window.

Transcription networks - Motifs in the integrated network of transcriptional relations and chromosomal adjacency.

What is still missing?

- Whole genome and whole network study.
- Uniform methodology, applicabale to all functional relations.
- Analysis of **additional functional relations** (e.g. PPIs, Complexes).
- Integrating the results into a **unified model** explaining gene organization.

- I Data
- II Concentration of co-functioning genes
- III Intra-chromosomal distances
- IV Spatial measures
- V Chromosome pairs and cancer

I - Data

Functional relations between genes: Expression, transcriptional relations, transcription factor and target gene, pathways, complexes, PPIs, miRNA networks...

Data: PPI, protein complexes and pathways



Steve Buckingham, 2004

 \sim 20,000 protein-coding genes from NCBI.

Data sets

We study 3 datasets of groups, a group is either

- Protein-Protein Interaction (PPI) from IntAct
 - 31,375 sets of Human genes whose products interact.
 - Size: 2 genes.

• Protein complexes from CORUM

- 1,520 sets of genes whose products form a Human protein complex;
- Size: between 2 and 142 genes (average=5.1 genes).

• Pathways from Reactome and KEGG

- 650 and 206 sets of genes whose products are present in the same Human pathway.
- Size: between 2 and 345/1122 genes (average=24/69.1 genes).

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Concentration of co-functioning genes

Intra-chromosomal distances Spatial measures Chromosome pairs and cancer

Tests Results

II - Concentration of co-functioning genes

Concentration of co-functioning genes

Intra-chromosomal distances Spatial measures Chromosome pairs and cancer **Tests** Results



Relative position of co-functioning genes whole-genome whole-network analysis.

- **Define test function**: Average of number of chromosomes involved in each group.
- Calculate the function value in the real genome.
- Estimate the probability to observe a value or higher (or smaller) for **random gene order**.

Concentration of co-functioning genes Intra-chromosomal distances

Tests Result:

1 mega-simulations

A permutation of the whole genome.

We change the order of gene in the whole genome.

Spatial measures



Figure: One genome with 3 chromosomes and 13 genes. One group with 4 genes: (3, 4, 8, 13). Concentration of co-functioning genes Intra-chromosomal distances

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We change the order of gene in the whole genome.

Spatial measures



Figure: The genome after a genome permutation One group with 4 genes: (3, 4, 8, 13).

Significant results: Number of chromosomes involved

The groups are significanlty involved in few chromosomes for IntAct, KEGG and CORUM. (P-values: 0.0107 for IntAct, 0.0788 for CORUM, < 0.00001 for KEGG and 0.0072 for Reactome).

Conclusion

On average, pathways and PPIs tend to involve significantly smaller number of chromosomes than expected at random.

Can we find a more informative test function?

Concentration of co-functioning genes

Intra-chromosomal distances Spatial measures Chromosome pairs and cancer Tests Results

Significant results: Cumulative distribution



Figure: Cumulative distribution of the number of chromosomes involved in a pathway for the real genome (red curve) and for the average over 10^6 random genome (blue curve). The error-bars denote the standard deviation.

Concentration of co-functioning genes

Intra-chromosomal distances Spatial measures Chromosome pairs and cancer Tests Results

Significant results: Cumulative distribution

- Complexes Tend to involve a single chromosome (Pvalue 0.0025).
- PPIs Pairs tend to lie on the same chromosome (Pvalue 0.0083).
- Pathways Tend to involve fewer chromosomes than expected at random. The effect becomes statistically significant from 5 chromosomes for Kegg and from 2 chromosomes for Reactome (Pvalue 0.013, 0.04 after correction for multiple test).

Definitions Tests Results

III - Intra-chromosomal distances

Definitions Tests Results

Intra-chromosomal distances - Definition

Let $d_{i,j}$ be the distance between genes *i* and *j*.

Intra-chromosomal distances

Pairs of genes along the same chromosome.

• For one pair of genes (i, j) along one chromosome: $d_{i,j}$ such that *i* preceded *j*, is equal to the number of *bases* between the end of *i* and the beginning of *j*.

Definitions Tests Results

Intra-chromosomal distances - Definition

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Intra-chromosomal distances

Pairs of genes along the same chromosome.

• For one group and one chromosome: The distance is $\sum_{i=1}^{n-1} \sum_{j=i+1}^{n} d_{i,j}/(n(n-1)/2).$

Definitions Tests Results

Intra-chromosomal distances - Definition

Let $d_{i,j}$ be the distance between genes *i* and *j*.

Intra-chromosomal distances

Pairs of genes along the same chromosome.

• For one group in the genome: The group distance is the average of chromosomal distances for all chromosomes containing at least two genes of this group.

Definitions **Tests** Results

Intra-chromosomal distances - 1 mega-simulations

One permutation by chromosome.

We change the order of genes inside each chromosome.



Figure: One genome with 3 chromosomes and 13 genes. One group with 4 genes: (3, 4, 8, 13).

Definitions **Tests** Results

Intra-chromosomal distances - 1 mega-simulations

One permutation by chromosome.

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Figure: The genome after chromosome permutations One group with 4 genes: (3, 4, 8, 13).

Definitions Tests Results

Intra-chromosomal distances - Results

Data set	p-value	
Reactome	$< 10E^{-05}$	
KEGG	$< 10E^{-05}$	
CORUM	$7.2E^{-04}$	
IntAct	0.0986	

Table: $P(d'_i \leq d)$ for intra-chromosomal distance of 4 data sets.

Conclusion

The co-functioning genes from pathways or protein complexes are **close** along chromosomes.

Definitions Tests Results

Significant results: Histogramme



Figure: Normalized histograms of the average intra-chromosomal distance in Mega BP between genes from the same group compared to average over random genomes for KEGG.

Concentration of co-functioning genes Previous work Intra-chromosomal distances Definitions Spatial measures Chromosome pairs and cancer Results

IV - Spatial measures

Previous work Definitions Tests Results

Spatial measures - 3D Human genome

3D genome [Lieberman-Aiden et al., 2010, Eitan and Amos, 2011]

- The Hi-C method probes the 3-dimensional architecture of whole genome.
- They obtain intra- and interchromosomal **contact probability**.
- Every chromosome is decomposed into **regions of 1 mega-bases**.



Previous work Definitions Tests Results

Spatial measures - 3 measures

We compute 3 spatial measures.

Let $m_{i,j}$ is one of these measures between the genes *i* and *j*.

3 spatial measures

The genes of one pair can be in different chromosomes.

• For one pair of genes: Average of Pearson correlation

• For one group: Average of $m_{i,j}$



Previous work Definitions Tests Results

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The genes of one pair can be in different chromosomes.

- For one pair of genes: Average of Pearson correlation
- For one group: Average of $m_{i,j}$ measureAll: for all *i* and *j*.



Previous work Definitions Tests Results

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3 spatial measures

The genes of one pair can be in different chromosomes.

- For one pair of genes: Average of Pearson correlation
- For one group: Average of $m_{i,j}$ measureIntra: for all *i* and *j* in the same chromosome.



Previous work Definitions Tests Results

Spatial measures - 3 measures

We compute 3 spatial measures.

Let $m_{i,j}$ is one of these measures between the genes *i* and *j*.

3 spatial measures

The genes of one pair can be in different chromosomes.

- For one pair of genes: Average of Pearson correlation
- For one group: Average of $m_{i,j}$ measureInter: for all *i* and *j* in different chromosomes.



Previous work Definitions **Tests** Results

Spatial measures - 1 mega-simulations

Two types of simulation: Chromosome permutations and genome permutation.

We change the order of gene in the whole genome. \hookrightarrow For *measureAll*.

We change the order of genes inside each chromosome. \hookrightarrow For *measureIntra* and *measureInter*.



Figure: One genome with 3 chromosomes and 13 genes.

One group with 4 genes: (3, 4, 8, 13).

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Previous wor Definitions Tests **Results**

Spatial measures - Results (1 Mega simulations)

	measureAll	measureIntra	measureInter
Reactome	$< 10E^{-06}$	< 10E - 06	2.81E-01
KEGG	< 10E - 06	< 10E - 06	6.18E-01
CORUM	1.00E-05	1.00E-06	1.05E-01
IntAct	1.50E-05	8.36E-04	1.63E-02

Table: $P(m'_i \le m)$ for 3 spatial measures of 4 data sets.

Conclusion

Co-functioning genes are significantly **close** in the space (in particular for genes along same chromosome).

Previous wor Definitions Tests **Results**

Comparison between intra-chromosomal distance and intra-chromosomal spacial measure



red: Co-functioning pairs of genes, blue: random pairs of genes.

Previous wor Definitions Tests Results

Distribution of spacial measure between pairs of genes



blue: True genome, light blue: random genome.

Context Definitions Results

V - Chromosome pairs and cancer

Context Definitions Results

Cancers

Definitions

Tumor An abnormal proliferation of tissues. Cell transformation results including loss of cell cycle control, insensitivity to apoptosis, abnormalities in DNA repair.

Cancer The cells are distancing themselves from the lineage of origin - malignant tumor.



Context Definitions Results

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Nature 2009, Beroukhim et al.

Context Definitions Results

Protein stoichiometry

Two genes g_1 and g_2 with 2 copies of each in the genome, and their products, the proteins P_1 and P_2 .





[Katz et al. 1990]

STACK - STatistical Associations in Cancer Karyotypes

Previous work: A systematic assessment of associations among chromosomal aberrations in cancer karyotypes, Michal Ozery-Flato, Chaim Linhart, Luba Trakhtenbrot, Shai Izraeli and Ron Shamir. 2011.

Methods: Observation of aberrations in 15 000 karyotypes.

Results: There exist pairs of aberrations significantly correlated. The majority of them are gain/gain or loss/loss.

Context Definitions Results

STACK - STatistical Associations in Cancer Karyotypes



Context Definitions Results

Data - STACK

- For each pair of chromosomes, a **P-value** expresses its tendency to be:
 - co-gained or lost (Both),
 - co-gained (Gain) or
 - co-lost (Loss).

• Cancer type specificity:

- For all tissues (All) or for one type of cancer:
- Hematology (Hema),
- Lymphoma (Lymph),
- Solid (Solid).

Context Definitions Results

Data - Number of crossing interactions

For each pair of chromosomes, we compute the number of PPI (from IntAct) with one gene in each chromosome, i.e. the **number of crossing interactions**.

We compute this number for the Human genome and for 10^6 randomly permuted genomes to obtain a **P-value** which expresses statistical significance of the number of crossing interactions between the two chromosomes.

We want to evaluate the **correlation** between vectors of P-values from STACK and this new vector of P-values.

Context Definitions Results

Result: Correlations

- **positive correlation** for chromosome gains in solid tumor (Spearmans correlation = 0.23, p-value = 0.0002),
- **negative correlation** for chromosome gains in lymphoid disorders (Spearmans correlation= -0.22, p-value = 0.0004).

Second test: GSEA method.

Enrichment of the set of most-significantly co-gained (resp. co-lost) chromosome pairs among the most functionally related chromosomes.

Context Definitions Results

Results: Co-gained chromosome pair in solid tumors



Figure: Illustration of the functional linkage between chromosomes, with a red highlight of the 16 most-significantly co-gained chromosome pairs in solid tumors. Links width corresponds to the strength of their functional linkage.

For solid tumors, the set of most-significantly co-gained chromosomes is **remarkably enriched** among the highly functionally-related chromosomes (p-value $< 1E^{-08}$).

Conclusions

Conclusions

We study the organization of co-functioning genes in the Human genome.

Conclusion

- Co-functioning genes tend to involve a **small** number of chromosomes.
- Co-functioning genes tend to be **close** to each other along chromosome and in the space.
- Correlation between **co-gained in solid tumors** and number of **crossing interactions**; depending on cancer type.

Prospects

- Take into account tandem duplicated genes.
- Study of **specific** set of co-functioning genes.
- Analysis of additional functional relations (e.g. miRNA, expression, transcriptional network).
- Similar analysis in different **species**.
- Integrating the results into a **unified model** explaining gene organization.