



Spatial models built on non homogeneous Poisson Point Processes

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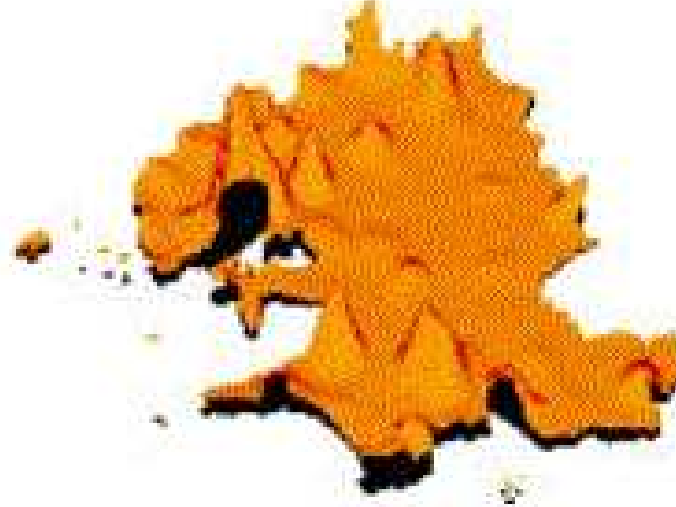
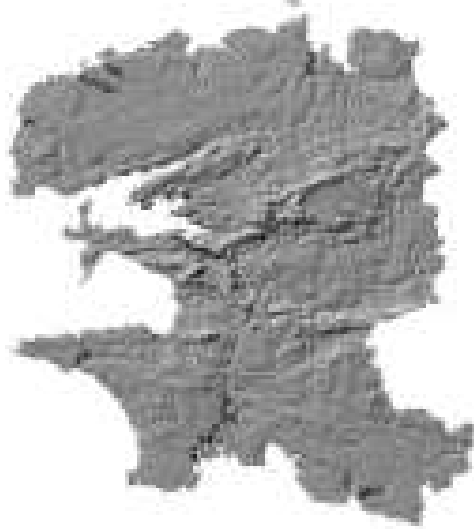
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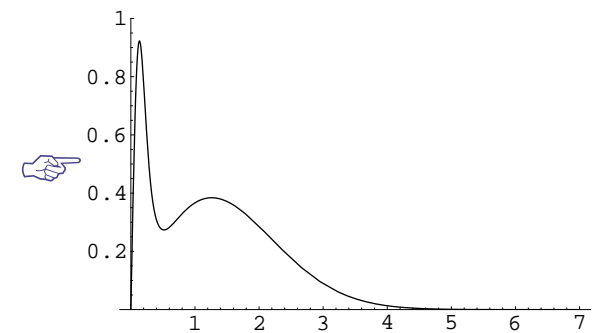
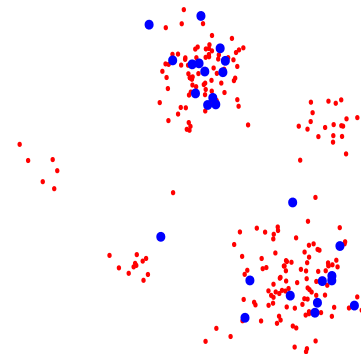
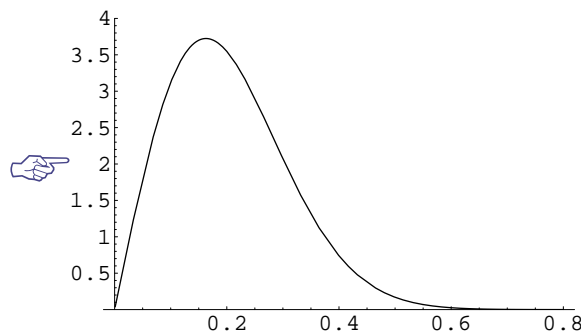
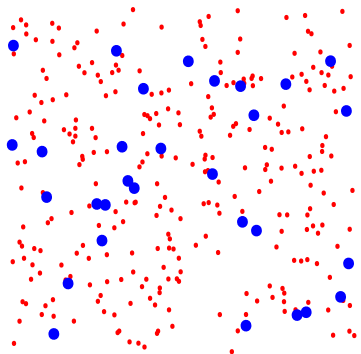


- Motivation
- Transform to/from homogeneity
- Toolbox for real situations analysis
- Conclusion



- repartition of population is non homogenous
- localization of network nodes follows accordingly
- this depends on the type of nodes and their hierarchical level

- so far, most telecommunication models assume spatial homogeneity
 - hierarchical models, Poisson Voronoï Agregated Tessellations. . .
 - road systems in the Stochastic Subscriber Line Model
- homogeneous models are useful
 - in some cases, ex : involving high level network nodes
 - as first order models to investigate faisability
- **spatial non-homogeneity can be structurant**
the cost of line of sight connection from node n (red) to closest node N (blue) depends on the length distribution





- need for practical methods to deal with spatial inhomogeneity
 - considering a variety of situations (shape, location)
 - considering a great number of parameters
 - computationally rapid
 - based on parameters that can be inferred from reality
- several theoretical approaches are possible
 - modulated Poisson
 - perturbation of Poisson-based models
 - transform of homogeneous planar Poisson Point Processes (PPP)
 - ...



- an **homogeneous** PPP (noted N)
 - is defined by its constant intensity in $\mathbb{R}^2 (= E)$
$$\beta\lambda(du)$$
- a **non-homogeneous** PPP
 - is defined by its non constant intensity in $\mathbb{R}^2 (= F)$
$$\mu(dx) = p(x)\lambda(dx)$$
 - is an image-process $X(N)$ in $F = X(E)$
- the **transform** X
 - must be a bicontinuous bijection
 - must be unique \rightarrow additional constraints
 - can be analytically computed in some cases



- **computation** of the transform X

- measures μ and λ are images $\mu = X(\lambda) \Leftrightarrow \lambda = X^{-1}(\mu)$

$$\int_D \lambda(du) = \int_D X^{-1}(\mu)(du) = \int_{X(D)} \mu(dx)$$

- usual change of variables with Jacobian $J_{X^{-1}}$

$$\int_D \lambda(du) = \int_{X(D)} |\det J_{X^{-1}}(x)| \lambda(dx)$$

- partial derivative equation $p(x_1, x_2) = |\det J_{X^{-1}}(x_1, x_2)|$
- specification of invariant 1D-sets ensures unicity
 - lines parallel to one axis
 - lines radiating from a center

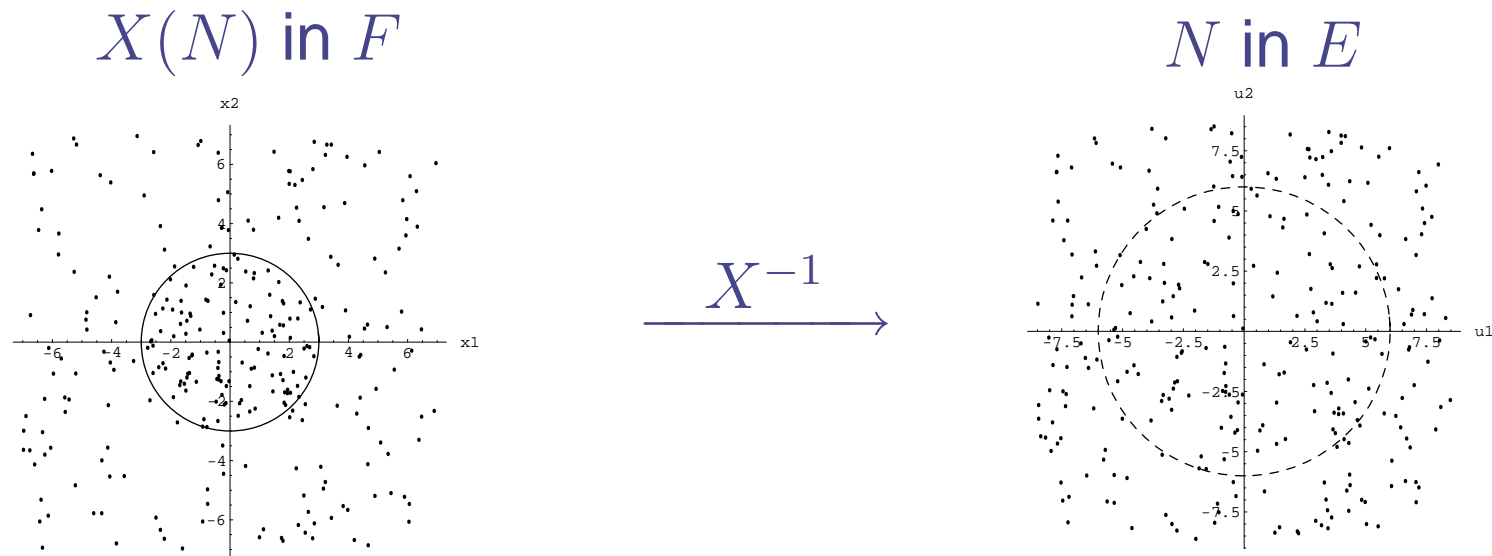
Transform to/from homogeneity



- **example** : discontinuous circle, radial transform
- non homogeneous $X(N)$ in F , intensity $\mu(dx) = p(x)\lambda(dx)$

$$p(x) = \{\alpha \text{ if } x \in \text{disc } \Gamma(0, R), \text{ else } \beta\}$$

- transformation to homogeneous X in E

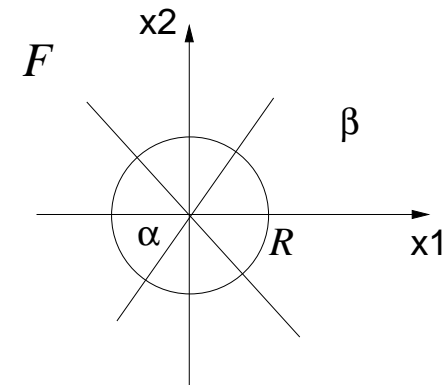


Transform to/from homogeneity

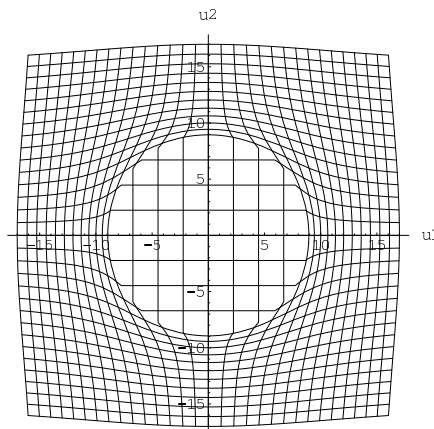


- **example** : discontinuous circle, radial transform
- radial invariance (centered in O) demands

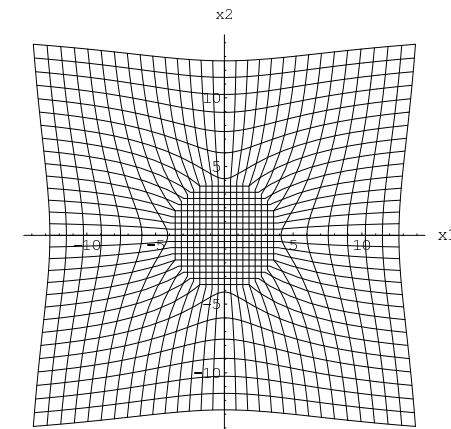
$$(u_1, u_2) = X^{-1}(x_1, x_2) = \phi(x_1, x_2)(x_1, x_2)$$



- unique solution $\phi(x_1, x_2) = \{ \sqrt{\alpha} \text{ if } x \in \Gamma, \sqrt{\beta + (\alpha - \beta) \frac{R^2}{x_1^2 + x_2^2}} \text{ else } \}$



iso- x_i curves in E , from X^{-1}



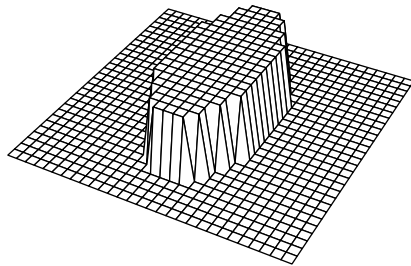
iso- u_i curves in F , from X

Transform to/from homogeneity

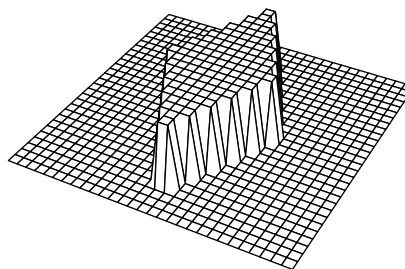


- analytical expressions are available for simple parametric shapes

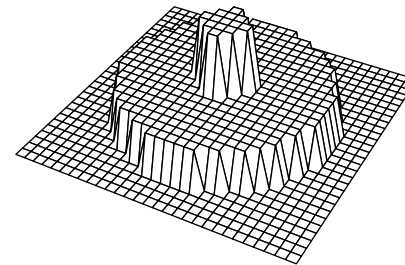
- discontinuous densities :



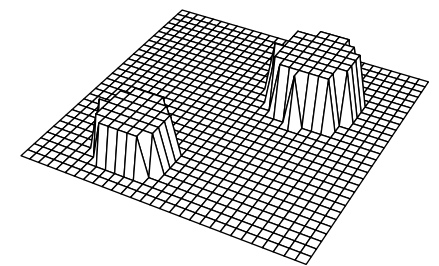
ellipsis



diamond

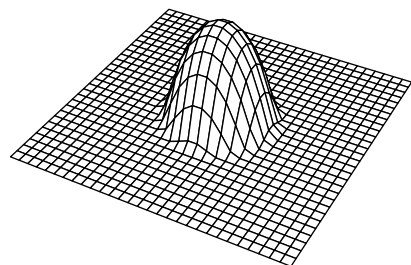


cake

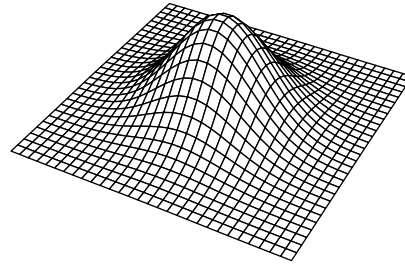


2 circles

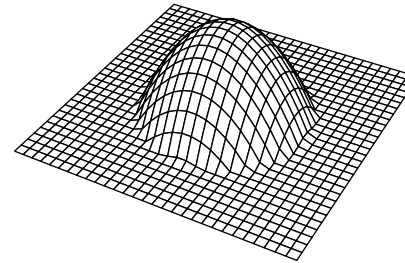
- continuous densities :



bell



gaussian



Epanechnikov

- radial and/or parallel transform whenever possible

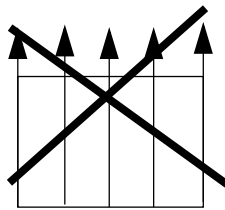
Transform to/from homogeneity



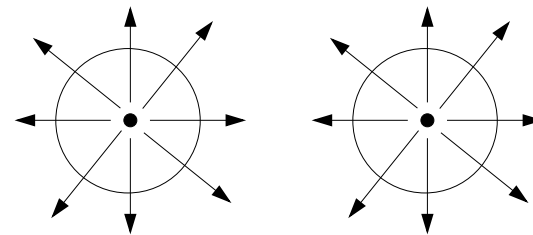
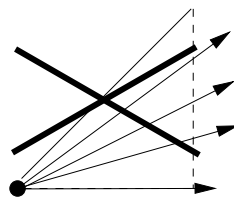
- exact transforms can easily be derived in other cases
 - direct calculation for complicated single shapes (ex general polygons)
careful choice of invariant varieties
 - modification of existing results by changing
the intensity levels, rescaling both coordinates
the shapes and locations, translation and/or flattening ...

- **this does not cover all our needs**

- some cases cannot be solved exactly



continuity is not verified



no exact transform for the set



the idea is to describe complex situations by mixing
approximate & exact forms
analytical & numerical results

- the "toolbox" contains
 - far field approximation
 - formal definition from induced metrics
 - application to model juxtaposition and superposition
 - "numerical" tools
 - fast realizations of non homogeneous PPP
 - transformation/construction of geometric figures
 - "analytical" tools
 - formal reuse of homogeneous results

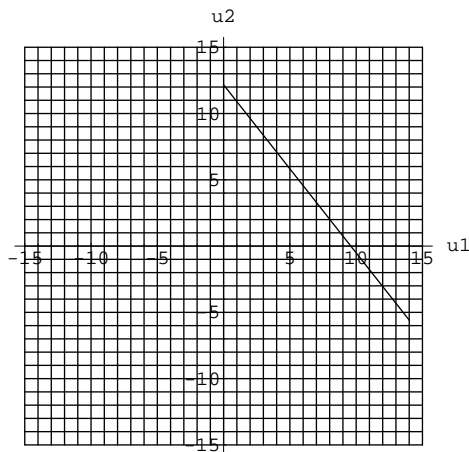


● induced metrics

recall: N in E intensity $\beta\lambda(du)$, $X(N)$ in F intensity $p(x)\lambda(dx)$

E , Euclidian metric

$$ds^2 = \eta_{ij} du_i du_j$$

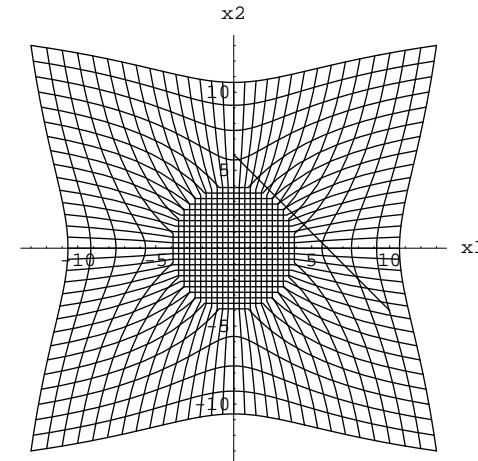


$$x = X(u)$$

$$g_{\mu\nu} = \eta_{ij} \frac{\partial u_i}{\partial x_\mu} \frac{\partial u_j}{\partial x_\nu}$$

F , induced metric

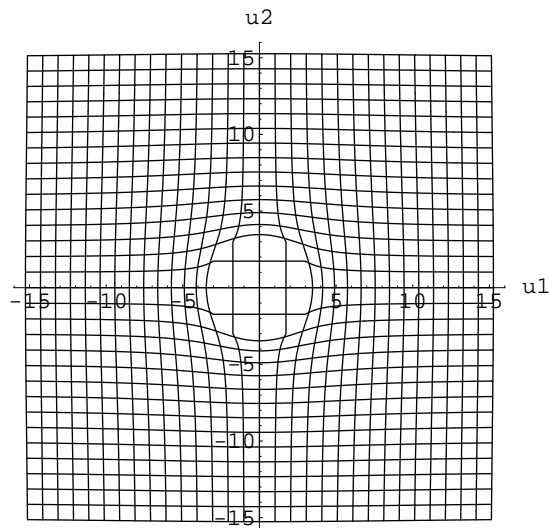
$$ds^2 = g_{\mu\nu} dx_\mu dx_\nu$$



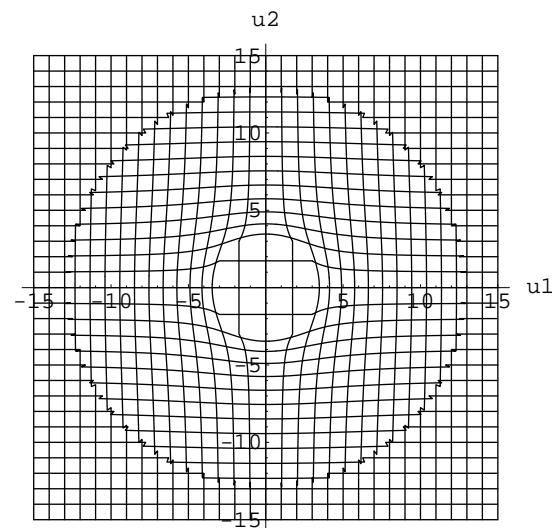
- metric g is location dependant and defined from p and its parameters
- metric g is continous and can be written analytically
- several other metrics can be defined in E and F
 - induced from X or X^{-1}
 - considering Euclidian or polar coordinate systems



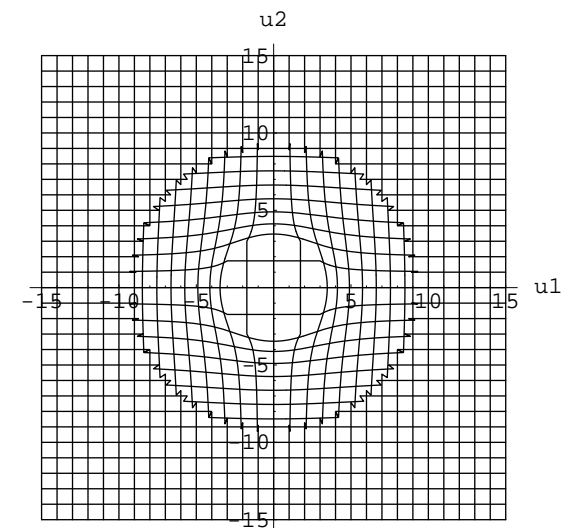
- formal definition of far field limit
 - compare natural polar metric δ and induced polar metric m
 - relative error $(\delta - m)/\delta < \epsilon$ farther from O than $D(\epsilon)(= R\sqrt{\frac{(\alpha-\beta)}{\beta\epsilon}}$ for circle)
 - stitching together homogeneous and non-homogeneous spaces
 - example : gaussian density $\alpha = 5, \beta = 1, R = 2$, iso- x_i curves in E



no stitching

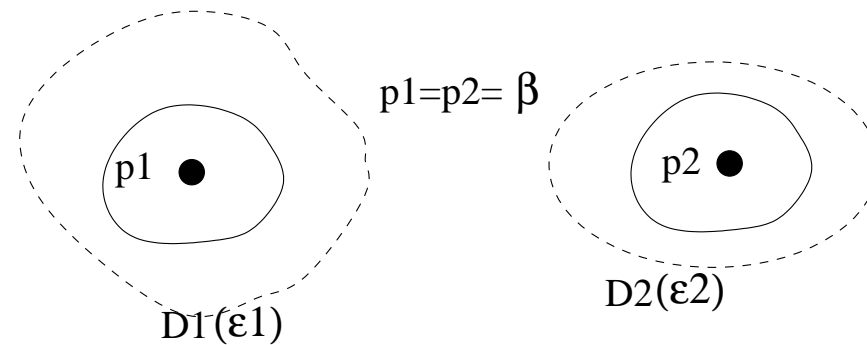


$\epsilon = 0.05, D = 12.6$

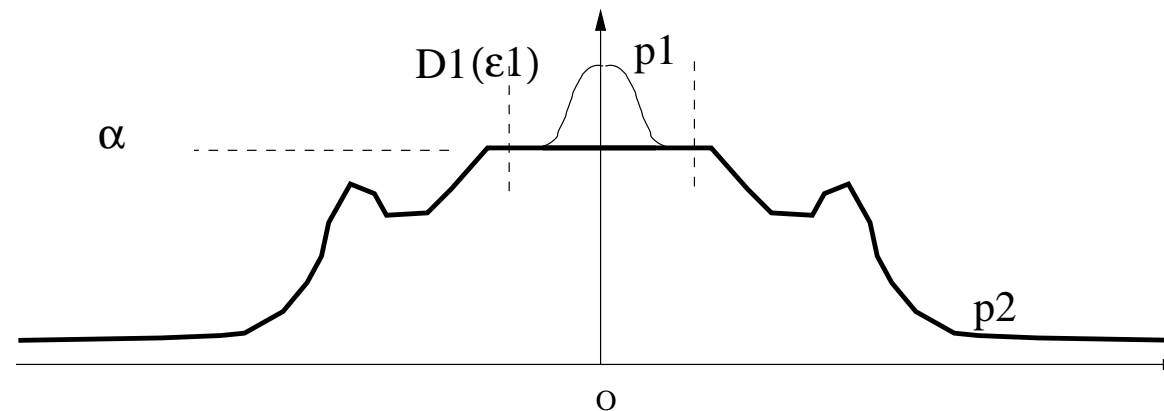


$\epsilon = 0.1, D = 8.9$

- approximate transforms using far field assumption
 - the transform affects points closer than $D(\epsilon)$
 - juxtaposition same basis intensity

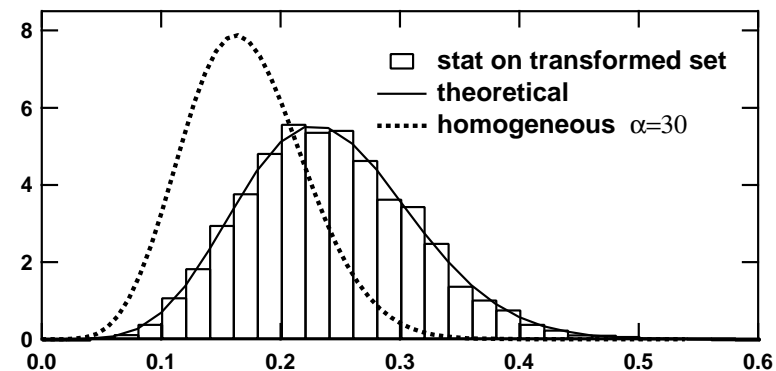
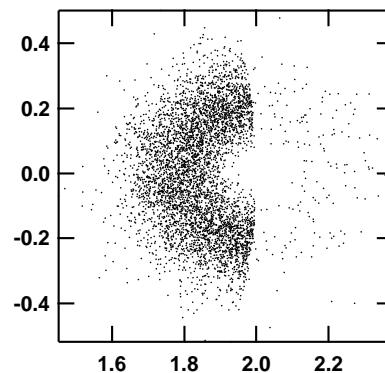


- superposition





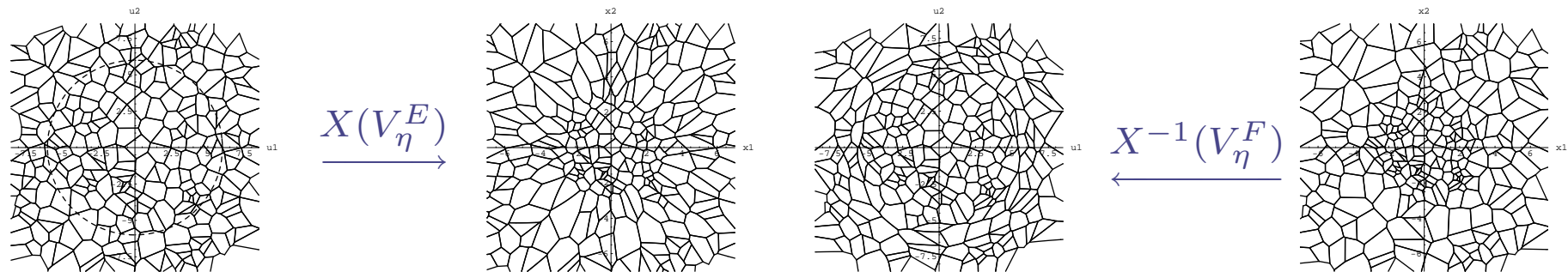
- fast generation of realizations of non-homogeneous PPP
 - generate one reference set \mathcal{U} homogeneous PPP of unit intensity
 T radial simulations, coordinates of n points closest to O
 - compute $X(\mathcal{U})$ to build the non homogeneous set
- statistics on non-homogeneous PPP
 - example : distances between point A and the 3rd closest point from $X(N)$
observe hom. N from $X^{-1}(A)$, translation $\mathcal{U}_A = \mathcal{U} + X^{-1}(A)$
compute $X(\mathcal{U}_A)$ and order distances to A , extract the third item
 $\alpha = 30, \beta = 1, R = 2, A = (2, 0)$ located on the circular discontinuity





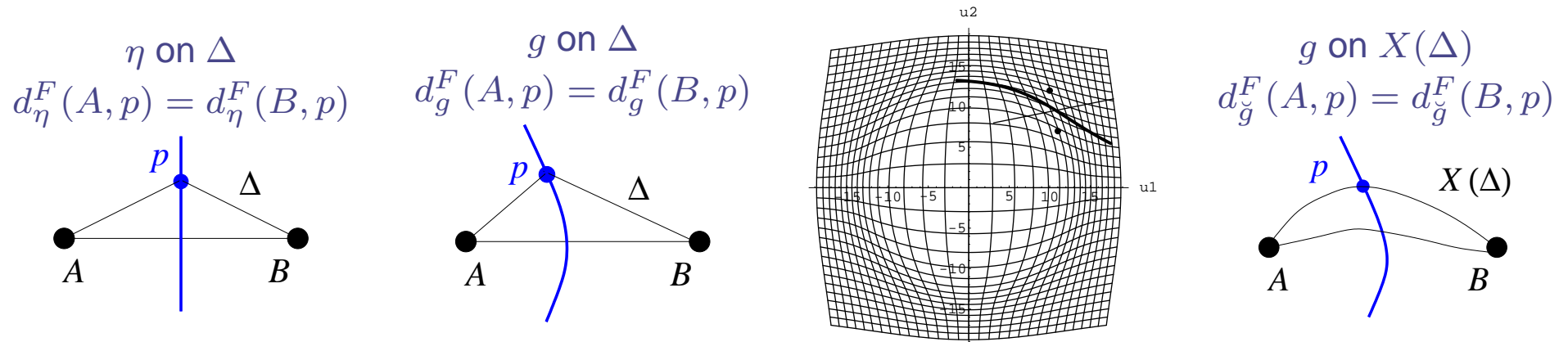
transformation of geometric figure (Voronoi tessellation)

- Euclidian η on straight Δ : nuclei from $N \rightarrow V_\eta^E$, nuclei from $X(N) \rightarrow V_\eta^F$



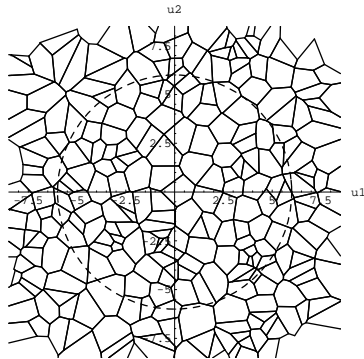
drawing of general bisectors

- use non euclidian metrics and/or transforms of straight lines Δ in algorithms





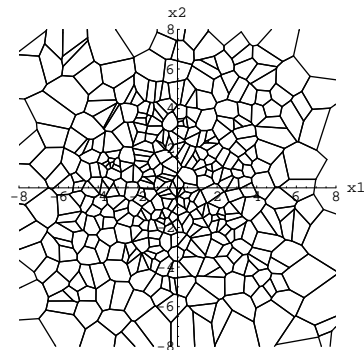
- metrics provide formal identity of writing
- average area of Poisson Voronoï cell, nucleus in A



V_η^E , polar metrics δ_A centered in A and δ_z

$$\mathcal{A}^E(A) = \iint_E dz \sqrt{|\det(\delta_A(z))|} e^{-\iint_{\Gamma(z)} dz' \sqrt{|\det(\delta_z(z'))|}} = \frac{1}{\beta}$$

same rule for bisectors : keep δ_A different nuclei location $N \rightarrow X(N)$: change δ in m



V_η^F , δ_A and induced polar metric centered y m_y

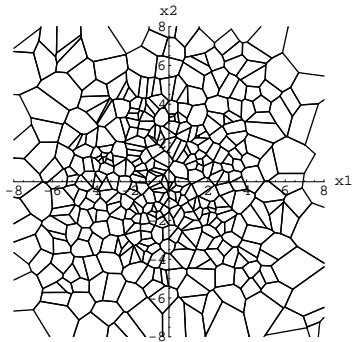
$$\mathcal{A}^F(A) = \iint_F dy \sqrt{|\det(\delta_A(y))|} e^{-\iint_{\Gamma(y)} dy' \sqrt{|\det(m_y(y'))|}}$$

- remarks

not too useful for areas ($\sqrt{|\det(m)|} \Leftrightarrow p$)

re-use of sensible multiD integration codes may not be straightforward

● computation and fitting of tessellation characteristics



● example : characteristics of Poisson Voronoi cells

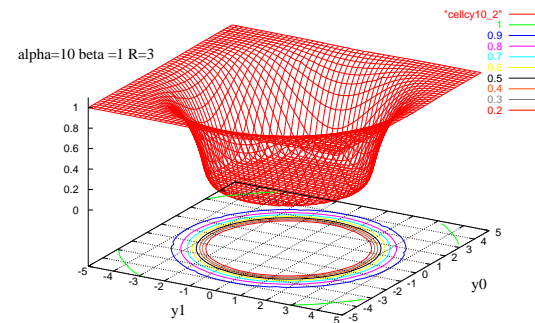
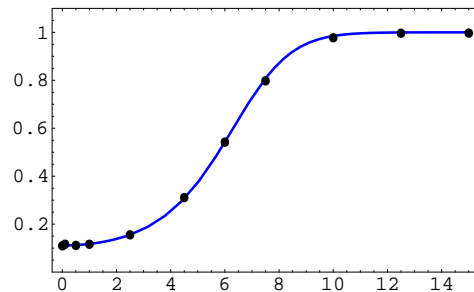
V_{η}^F tessellation

average area $\mathcal{A}^F(A)$ of cell nucleus in A

average perimeter $\mathcal{P}^F(A)$

● study the dependance on A and on the density shape and parameters
circular discontinuity

gaussian density area



● approximations for smooth densities : ex gaussian case $\mathcal{A}^F(A) \sim 1/p(A)$

● build a library from fitted results making the most of symmetries



- explicit transforms and induced metrics allow
 - to re-use results from homogeneous PPP : same formal writing
 - to be introduced in algorithms → radial simulation of "typical" cells...?
- practical interest for France Telecom
 - gather a set of formulas and tools adapted to spreadsheet codes
 - no need of random generators to generate points of non homogeneous PPP
 - analysis of complex situations
 - by mixture of approximations, fitted and exact results
- perspective
 - working on length distributions
 - analysis of tessellations characteristics
 - consider several hierachical levels of non homogeneous PPP
 - homogenization technique is not limited to PP



- homogeneous hierarchical stochastic telecommunication models
 - F. Baccelli, M. Klein, M. Lebourges and S. Zuyev
Stochastic geometry and architecture of communication networks
Telecommun. Syst. 7 pp209-227 (1997)
 - K. Tchoumatchenko and S. Zuyev
Aggregate and fractal tessellations
Probab. Theory Relat. Fields 121, pp198-218 (2001)

- road systems in the Stochastic Subscriber Line Model
just have a look on <http://www.geostoch.de>

- computation of the transform
 - R. Senoussi, J. Chadoeuf and D. Allard
Weak Homogenization of point processes by space deformations
Adv. Appl. Prob. (SGSA) 32 pp. 948-959 (2000)

Thank you for your attention !