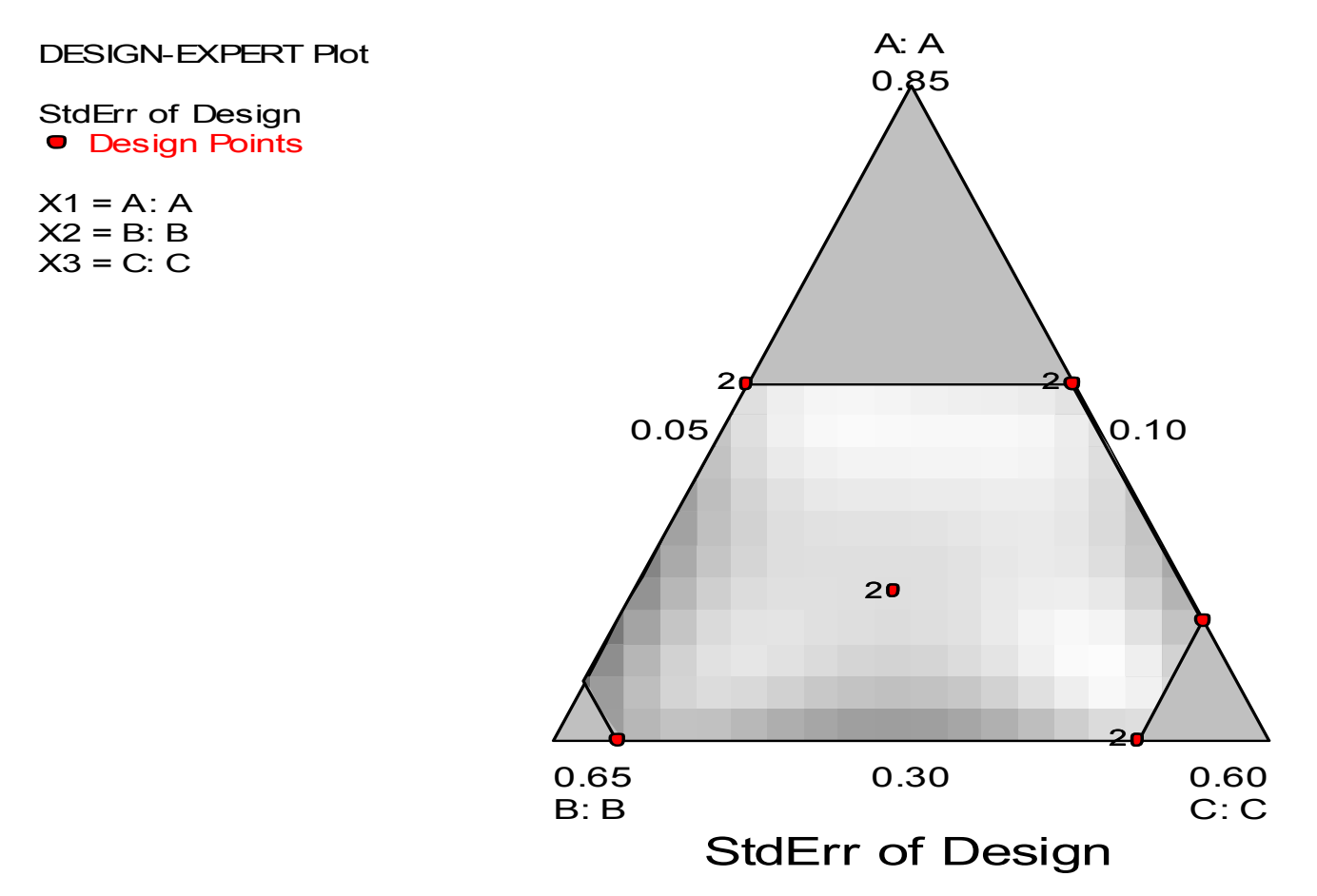


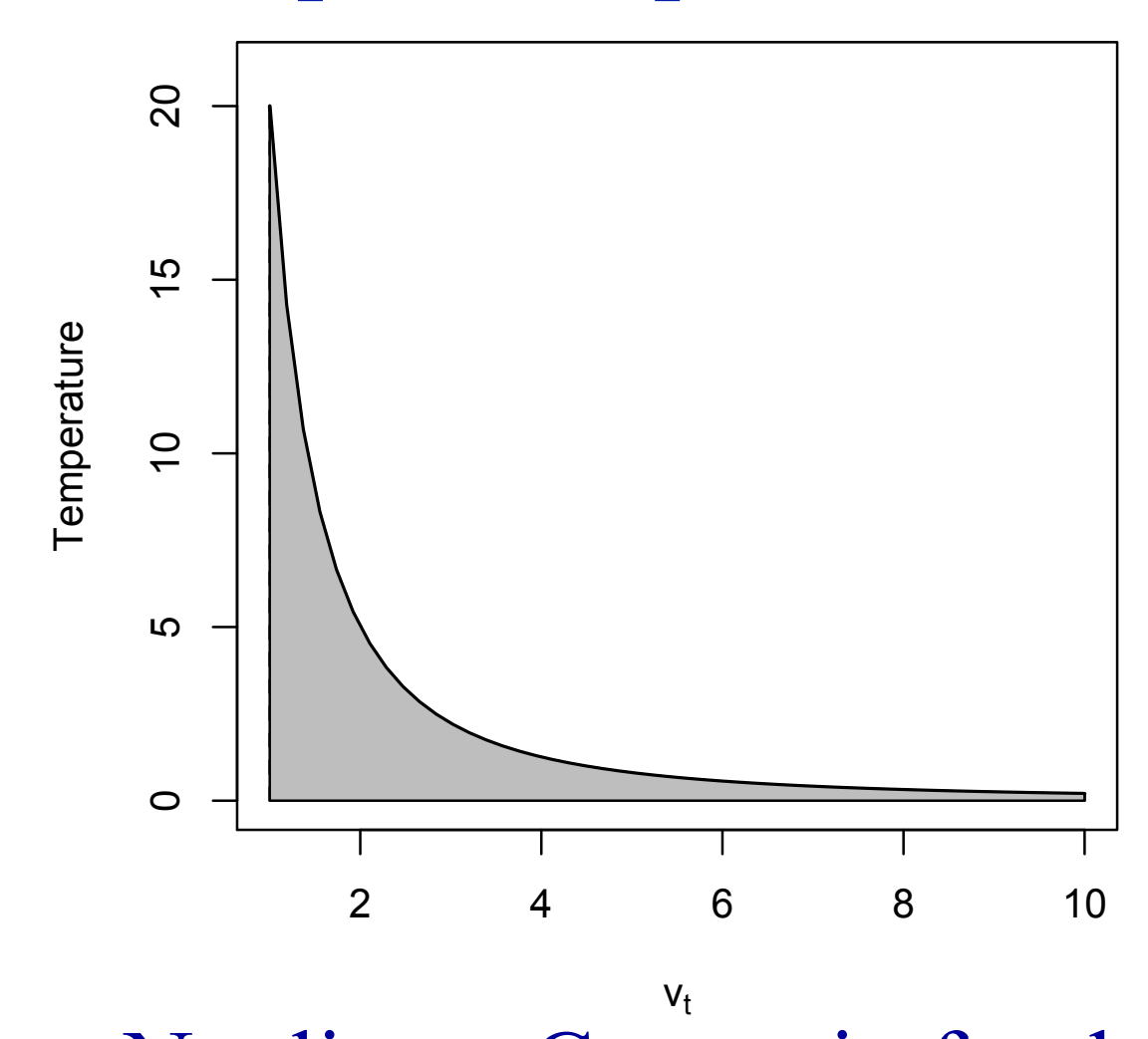
Motivations

- Physical Experiments: mixture experiments. (Cornell, 2002)



Linear Constraints only!

- Computer Experiments



More Complex Constraints!

E.g. Nonlinear Constraint for the Mathematical Model for the Low Pressure Chamber.

Literature on Constrained DOE

- Physical Experiments:
 - Mainly are mixture experiments (Cornell 2002)
 - Montgomery et al. (2002): bond strength of adhesive
 - Hung et al. (2010) and Hung (2011)

All methods are for linear constraints only!

- Computer Experiments:
 - Sasena et al. (2002): applied optimization
 - Trosset (1999) and Stinstra et al (2003)
 - Draguljic, Dean, and Santner (2012)

Can work for nonlinear Constraints. But need to generate huge candidate set!

Can work for nonlinear Constraints. But need advanced NLP solver!

Not accessible or Inefficient!

Coordinate-Exchange Algorithm

- Finding the optimal coordinate is a one-dimension optimization problem, easier and less computational!
- No sophisticated NLP solvers are needed.
- Coordinate-exchange method can handle broader range of constraints.
 - Fix all the other p-1 dimensional variable value and vary only one variable value.
 - If the p-dimensional constraints are convex, then the projected one-dimension feasible region becomes a single-interval set.
 - If the p-dimensional design space are non-convex or disconnected, then the one-dimension feasible region contains multiple intervals.
- Exchanging one coordinate of the design leads to less computation in updating the objective function.

Simulated Annealing (SA) Algorithm

- Randomize the selection of coordinate $D_{i,j}$ to exchange.
- Always accept improvement, but also accept the setback with a probability.
- Simulate the metal cooling process, in order to avoid local optimum.
- Initial temperature T_0 : large, specified according to the setting of the design.
- Rate of temperature decreasing β between [0.96, 0.99].

Coordinate-Exchange SA Algorithm

D: the design matrix of size n-by-d; Ω is the d-dimension constrained space; x_i is the design point in Ω ; $\psi(\cdot)$ is design criterion.

Set the tuning parameters of SA algorithm T_0 , β , and $T\epsilon$. Construct the initial design D.

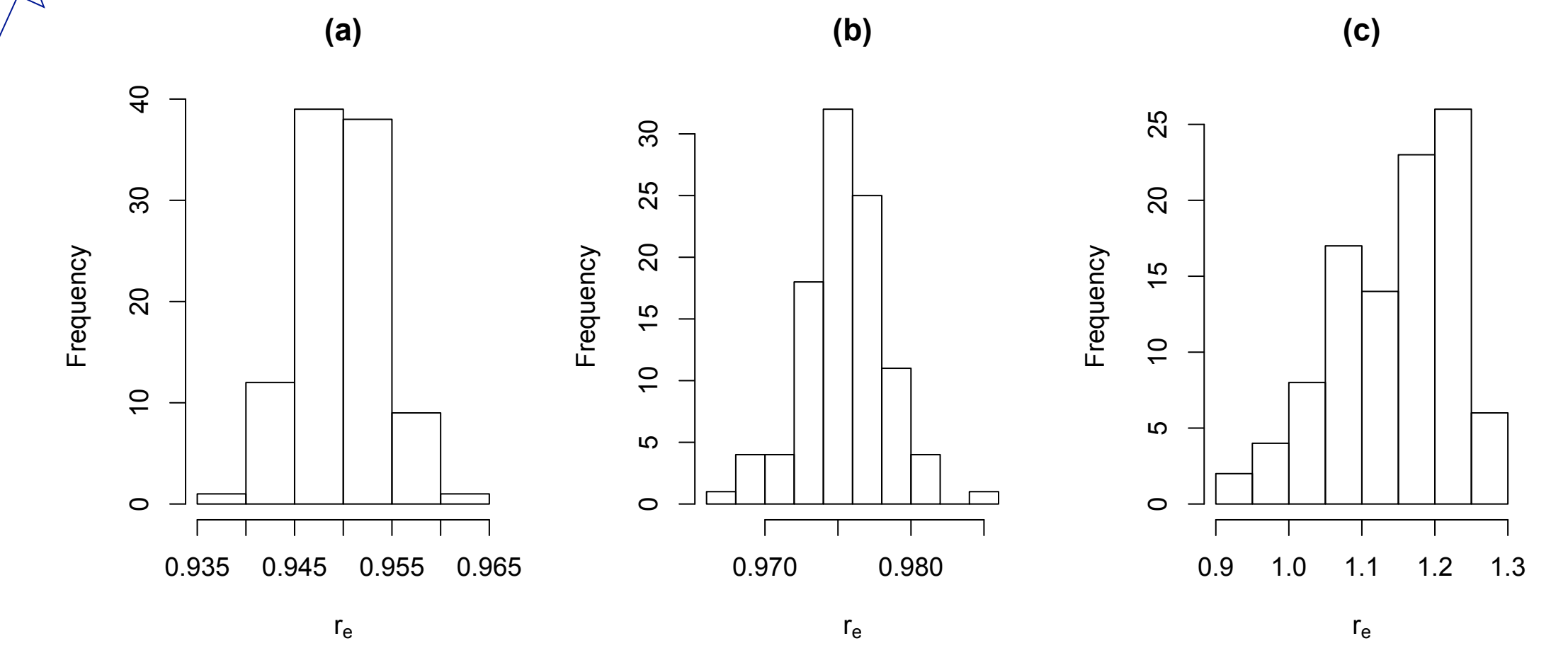
Compute the row deletion function $d_r(x_i)$ for each row x_i and column deletion function $d_c(X_j)$ for each column X_j . Random choose the row i^* and column j^* with probabilities proportional to $d_r(x_i)$ and $d_c(X_j)$.

Denote the delta function $\Delta(x_{i^*j^*}, x)$ as the measurement of improvement of the design criterion by exchanging the coordinate $x_{i^*j^*}$ with another value x . Solve the optimization problem:

Min or Max $\Delta(x_{i^*j^*}, x)$ s.t. x in $\Omega_{j^*}(x_{i^*})$, where $\Omega_{j^*}(x_{i^*})$ is the projected constraints for $x=x_{i^*}$. Deonte the optimal solution as x^* .

Iterate Step 1-3 until $T < T\epsilon$. Return the current design D as the optimal design with the optimal criterion $\psi(D)$.

Exchange the optimal solution x^* with $x_{i^*j^*}$ according to the probability $\pi = \min\{1, \exp(-\Delta(x_{i^*j^*}, x^*)/T)\}$. Then update all the deletion functions and design matrix. Update the temperature $T \leftarrow T\beta$.



Histogram of efficiencies of optimal designs returned by proposed method w.r.t. the ones returned by JMP. (a) D-optimal (b) A-optimal (c) ϕ_p space filling design. (with box constraints only!).

Three design-criterion

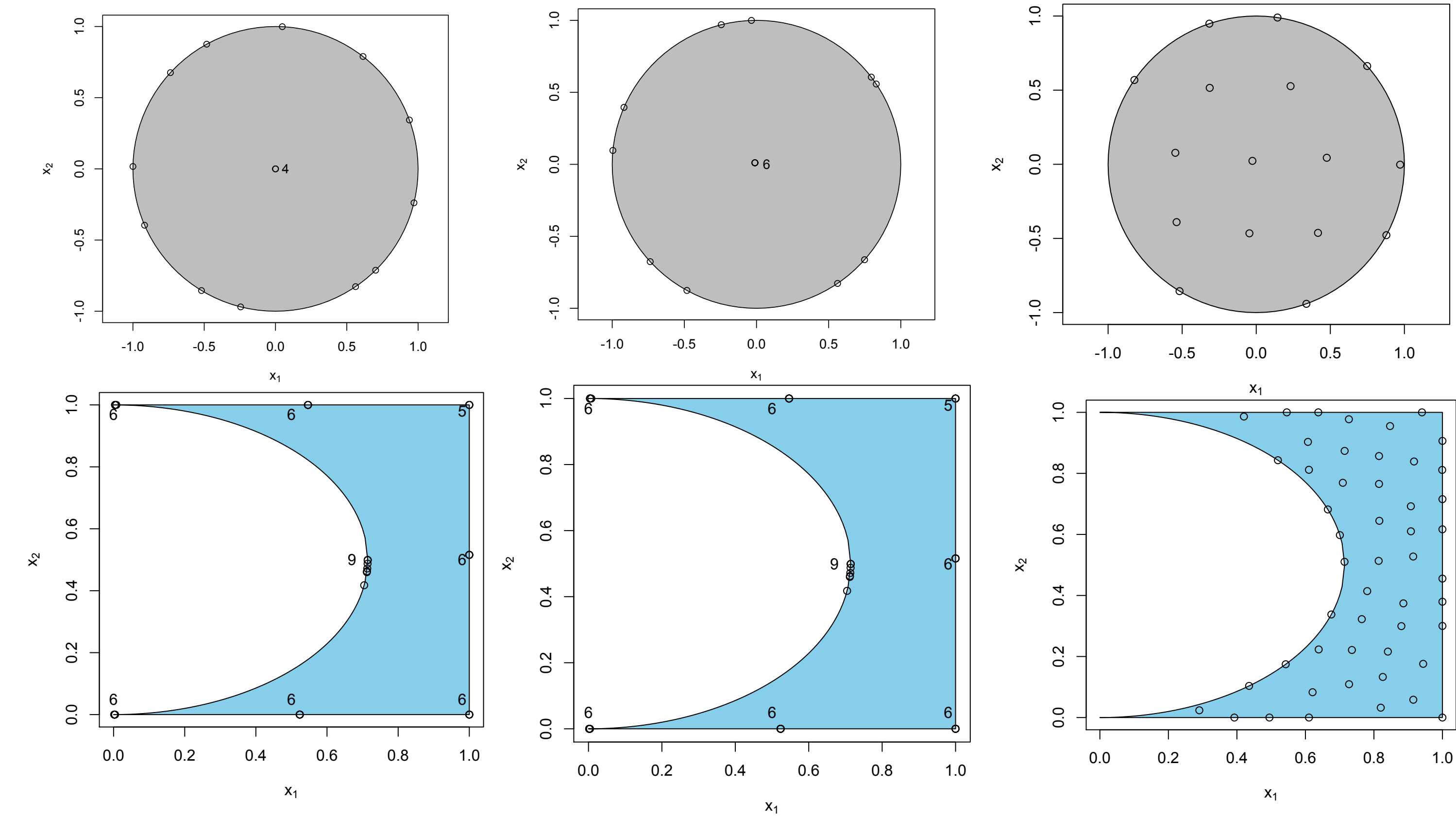
- D-optimal: $\psi(D) = \det(F^T F)$
- Linear-optimal: $\psi(D) = \text{tr}(M(F^T F)^{-1})$

ϕ_p space filling: $\psi(D) = \phi_p(D) = \left(\sum_{i,j=1}^n d(x_i, x_j)^{-p} \right)^{1/p}$

Need to derive the delta function, deletion functions, and updating formula for different criteria.

Examples

- Convex Constraint: $x_1^2 + x_2^2 \leq 1$
- Non-convex Constraint: $(0.7x_1)^2 + (x_2 - 0.5)^2 \geq 0.25$



D-optimal

A-optimal

Space Filling