# Diabetes Prediction with Incomplete Patient Data

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### Introduction

- Desirable to have minimal flexing in a building, which is determined by how well the supporting truss structure is built
- A truss is defined by the size and shape of bars, and their attachment points (i.e., nodes) in some physical space  $\mathcal{D} \subset \mathbf{R}^2$  (for a 2-D structure)
- Traditional approaches:
- Discretize the space for nodes:  $\hat{\mathcal{D}} \subset \mathbf{Z}^2$  (e.g., Ben-Tal & Nemirovski)
- Introduce complicated domain-specific heuristics (e.g., Wang et. al.)

# Truss Topology Optimization

#### Produce

- ullet Set of sized bars  ${\cal B}$  that constitute a truss
- Set of attachment points or nodes  ${\mathcal X}$  for the bars

#### Given

- Set of fixed nodes  $\mathcal{X}^{\mathsf{fixed}} \subset \mathcal{X}$  representing the truss foundation
- Set of loading forces  $\mathcal F$  that the truss is to be designed to support
- ullet Physical space  ${\mathcal D}$  that limits where  ${\mathcal X}$  can be placed
- Maximum allowable weight of truss  $W^{\mathsf{max}}$
- Structural symmetry constraints

To maximize the truss stiffness, which is related to the elastic stored energy  $\Theta(\mathcal{F}, \mathcal{U})$ , where  $\mathcal{U}$  is the set of node deflections under load forces

### Problem Formulation

The design variables for our truss optimization are:

- Cross sectional areas  $a \in \mathbf{R}^m$ , where  $a_i \in \mathbf{R}$  is the area of the  $i^{th}$  bar
- Coordinates  $x \in \mathbf{R}^{2n}$ , where  $x_j \in \mathbf{R}^2$  are the coordinates of the  $j^{th}$  node

#### Our problem data are:

- Loading forces  $F \in \mathbf{R}^{2n}$ , where  $F_j \in \mathbf{R}^2$  is the load on the  $j^{th}$  node
- Material densities  $\rho_1, \ldots, \rho_m \in \mathbf{R}$  of bars
- Young's moduli  $E_1, \ldots, E_m \in \mathbf{R}$  characterizing the elasticities of the bars
- Bar lengths  $L_1, \ldots, L_m \in \mathbf{R}$ , which are dependent on node coordinates x

#### (Cont'd)

- Force mapping matrix  $P(\mathcal{X}) \in \mathbf{R}^{m \times 2n}$ , which relates loads F to the internal stresses experienced by the bars,  $f \in \mathbf{R}^m$ ; implicit in P is an adjacency matrix relating each bar to its attachment points
- Stiffness matrix  $K(\mathcal{X}, a, L)$ , which determines the amount of flex in the truss

$$K = \sum_{i=1}^{m} \frac{E_i a_i}{L_i^2} p_i p_i^T,$$

where  $p_1, \ldots, p_m$  are the columns of the force mapping matrix P

Our truss design optimization is further characterized by the following variables, whose relations contain all of the physics of the problem:

- Node deflections  $u \in \mathbf{R}^{2n}$  due to the truss flexing under loads F, where  $u_j \in \mathbf{R}^2$  is the deflection of the  $j^{th}$  node; by Hooke's Law, we have the force balance F = Ku
- Internal stress  $f_i \in \mathbf{R}$  experienced by each bar due to the node deflections

$$f_i = -\frac{E_i a_i}{L_i^2} p_i^T u, \quad i = 1, \dots, m$$

• Stored elastic energy  $\Theta = \frac{1}{2}F^Tu$ , which we minimize in order to maximize the truss stiffness

## An Alternating Convex Optimization Approach

The minimization of  $\Theta$  in (a,x) that follows from our formulation above is non-convex. As a heuristic to solve the optimization problem, we first optimize over the bar sizes a, and then over the node coordinates x:

• We perform a linear change of coordinates to cast the bar sizing problem as a second-order cone program (SOCP) in  $w, v \in \mathbf{R}^m$ :

$$w_i + v_i = -\frac{1}{2} \left( u^T P \right)_i f_i,$$
$$w_i - v_i = a_i$$

The value of  $w_i + v_i$  is therefore the spring energy stored in the  $i^{th}$  bar

• Holding x constant, find the bar cross sectional areas a that minimize  $\Theta$ :

minimize 
$$\Theta = 1^T (w + v)$$
  
subject to  $Pf + F = 0$   
 $M(w - v) \leq d$   
 $\left\| \left( v_i, \frac{L_i}{\sqrt{E_i}} f_i \right) \right\|_2 \leq w_i, \quad i = 1, \dots, m$   
 $1^T (w - v) \leq W^{max}$  (1)

• We then perform an affine change of coordinates to cast the node positioning problem as an SOCP in  $w, v \in \mathbf{R}^m$  (different from above):

$$w_i + v_i = -\frac{1}{2} \left( u^T P \right)_i f_i,$$

$$w_i - v_i = \frac{2p_i^T y_i}{L_i} + 1$$

(Cont'd)

• Holding a constant, find a set of displacements  $y \in \mathbf{R}^{2n}$  that "shift" the node coordinates x from their original positions and minimize  $\Theta$ :

minimize 
$$\Theta = 1^T (w + v)$$
 subject to  $Pf + F = 0$  
$$\frac{1}{2} ((w_i - v_i) - 1) = \frac{p_i^T y_i}{L_i}, \quad i = 1, \dots, m$$
 
$$\left\| \left( v_i, \frac{L_i}{\sqrt{E_i a_i}} f_i \right) \right\|_2 \le w_i, \quad i = 1, \dots, m$$
 
$$\|y_i\|_2 \le \epsilon_i, \quad i = 1, \dots, m$$
 
$$g(y) = 0,$$
 (2)

where g(y) = 0 enforces truss symmetry, and  $||y_i||_2 \le \epsilon_i$  restrict node shifts.

In our heuristic, we first discretize the physical space as in traditional approaches to obtain  $\hat{\mathcal{D}}$ , and alternate between solving (1) and (2) in each iteration:

given 
$$\mathcal{X}^{\mathsf{fixed}}$$
,  $\mathcal{F}$ ,  $\hat{\mathcal{D}}$ 

Generate set of node coordinates  $x^0$  from  $\hat{\mathcal{D}}$ , set  $x := x^0$ 

repeat

1. Given  $x$ , obtain  $a$  and  $\Theta_1$  as the solution to and objective of (1)

2. Given  $a$ , obtain  $y$  and  $\Theta_2$  as the solution to and objective of (2), set  $x := x + y$ 

3. **break if**  $\Theta_1$  and  $\Theta_2$  converge

### Example: Bridge Design

This problem has 791 variables and 219 constraints. Out of several solvers, SCS was the fastest at 0.3 s per iteration (vs. 2.0 s with SeDuMi at comparable accuracy requirements). SCS's speed advantage scales with problem size (~100 times faster than SeDuMi with 16000 variables, 4000 constraints).

### Conclusion

Our alternating convex optimization approach presents a promising tool to solving the non-convex truss design problem. Future work should extend the model to 3-D and compare this approach to other existing methods.

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