COL866: Foundations of Data Science

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Ranking and Social Choice

- Problem: Merge multiple ranked lists in a meaningful manner.
- Here is a simple example that brings the difficulty of such a task.

Individual	**rank 1**	**rank 2**	**rank3**
1	a	b	c
2	b	c	a
3	c	a	b

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- Is a ranked higher than b?
- Is b ranked higher than c?
- Is a ranked higher than c?

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- So, such a task of combining individual rankings to come up with global ranking might be difficult in general. It would be great if we could argue this in general.
- For such an argument we need to fix the axioms of ranking, or some basic conditions that a global ranking should satisfy.

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  - Nondictatorship: The algorithm cannot always select one individual's ranking as the global ranking.
  - Unanimity: If every individual prefers a to b, then the global ranking should prefer a to b.
  - Independent of irrelevant alternatives: If individuals modify their rankings but keep the order of a and b unchanged, then the global order of a and b should not change.
- We will argue that it is not possible to satisfy all three axioms simultaneously (Arrow's Theorem).
- We start with a lemma.

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Lemma

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Individual	Ranking
1	abcd
2	abcd
3	bacd

Table: Individual 3 changing his ranking to bcda, changes the global ranking.

Compressed Sensing and Sparse Vectors

Compressed Sensing and Sparse Vectors

- A signal in the current context is a vector $\mathbf{x}$ of length d and a measurement of signal $\mathbf{x}$ is taking the dot product of $\mathbf{x}$ with a known vector $\mathbf{a}_i$.
- Claim: For uniquely reconstructing $\mathbf{x}$ without any assumptions, d linearly independent measurements are necessary and sufficient.
  - Given $A\mathbf{x} = \mathbf{b}$, solve for $\mathbf{x}$ by computing $\mathbf{x} = A^{-1}\mathbf{b}$.
- If there are fewer than d measurements and A has rank $< d$, there may be multiple solutions.
- Informal claim: If $\mathbf{x}$ is sparse with $s << d$ non-zero elements, then we might be able to reconstruct $\mathbf{x}$ with far fewer measurements.
- This is popularly known as compressed sensing and has applications in photography (where it reduces the number of sensors) and magnetic resonance imaging.

- Sparse vector: A vector $\mathbf{x} \in \mathbb{R}^d$ is said to be s-sparse if it has at most $s \leq d$ non-zero elements.
- Let us examine the conditions under which $A\mathbf{x} = \mathbf{b}$ has a unique sparse solution. The matrix A is an $n \times d$ matrix with $n < d$.
- Claim 1: Suppose there are two s-sparse solutions $\mathbf{x}_1$ and $\mathbf{x}_2$. Then $\mathbf{x}_1 - \mathbf{x}_2$ will be a $2s$-sparse solution to the homogeneous system $A\mathbf{x} = \mathbf{0}$.

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- Claim 2: Existence of a $2s$-sparse solution to $A\mathbf{x} = \mathbf{0}$ implies the existence of $2s$ columns of A that are linearly dependent.
- Combining claims 1 and 2, we get that if no $2s$ columns of A are linearly dependent, then there can only be one s-sparse solutions to $A\mathbf{x} = \mathbf{b}$.

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  Select each entry of A independently from the standard Gaussian.

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  - Try all possible $\binom{d}{s}$ locations for non-zero elements in $\mathbf{x}$ and solve $A\mathbf{x} = \mathbf{b}$. Unfortunately, this takes $\Omega(d^s)$ time.

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- Question: How do we obtain the s-sparse solution? Yes in $\Omega(d^s)$ time.
- Question: Can we find a sparse solution efficiently?

- Finding a sparse solution to $A\mathbf{x} = \mathbf{b}$ can be written as the following program:

$$\text{minimize } ||\mathbf{x}||_0$$
$$\text{subject to: } A\mathbf{x} = \mathbf{b}$$

- Unfortunately, this is not a convex program. Instead, the next program is a convex program. In fact, it can written as a linear program.

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- Claim 1: The following linear program is equivalent to the above program.

$$\text{minimize } \sum_i u_i + \sum_i v_i$$
$$\text{subject to: } A\mathbf{u} - A\mathbf{v} = \mathbf{b}, \mathbf{u} \geq 0, \mathbf{v} \geq 0$$

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  - If A is of a specific form, then the solution to the program gives a sparse solution.

- Program **P**:

$$\text{minimize } ||\mathbf{x}||_1$$
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- Question: How does solving the above program help in finding a sparse solution to $A\mathbf{x} = \mathbf{b}$?
  - If A is of a specific form, then the solution to the program gives a sparse solution.
- The following theorem states the conditions for matrix A under which the solution to **P** is an s-sparse solution $A\mathbf{x} = \mathbf{b}$.

Theorem

*If matrix A has unit-length columns $\mathbf{a}_1, ..., \mathbf{a}_d$ and the property that $|\mathbf{a}_i^T \mathbf{a}_j| < \frac{1}{2s}$ for all $i \neq j$, then if the equation $A\mathbf{x} = \mathbf{b}$ has a solution with at most s non-zero coordinates, this solution is the unique 1-norm solution to $A\mathbf{x} = \mathbf{b}$ (i.e., solution to program **P**).*

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- Such a matrix can be constructed efficiently using concepts developed in high dimensional geometry. The next theorem summarises everything.

Theorem

For some absolute constant c, if A has n rows for $n \geq cs^2 \log d$ and each column of A is chosen to be a random unit-length n-dimensional vector, then with high probability A satisfies the conditions of previous theorem and therefore if the equation $A\mathbf{x} = \mathbf{b}$ has a solution with at most s non-zero coordinates, this solution is the unique minimum 1-norm solution to $A\mathbf{x} = \mathbf{b}$.

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Proof sketch

- Claim: Let $\mathbf{x}_0$ denote the unique s-sparse solution to $A\mathbf{x} = \mathbf{b}$ and let $\mathbf{x}_1$ be a solution of smallest possible 1-norm. Let $\mathbf{z} = \mathbf{x}_1 - \mathbf{x}_0$. Then $\mathbf{z} = \mathbf{0}$.

End