NDBI021 User preferences

substantially modified this year

One third Peter Vojtáš, KSI MFF UK

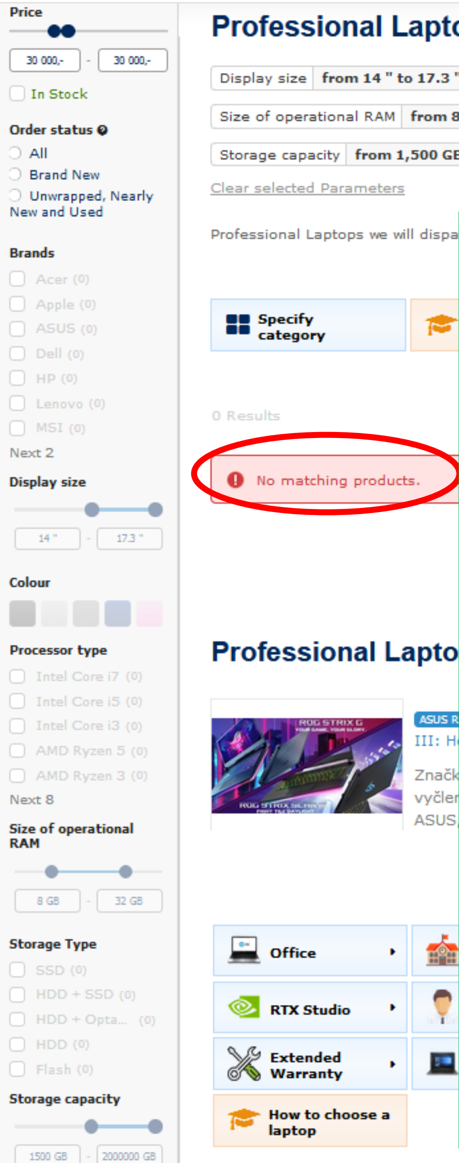
11/14 Introduction

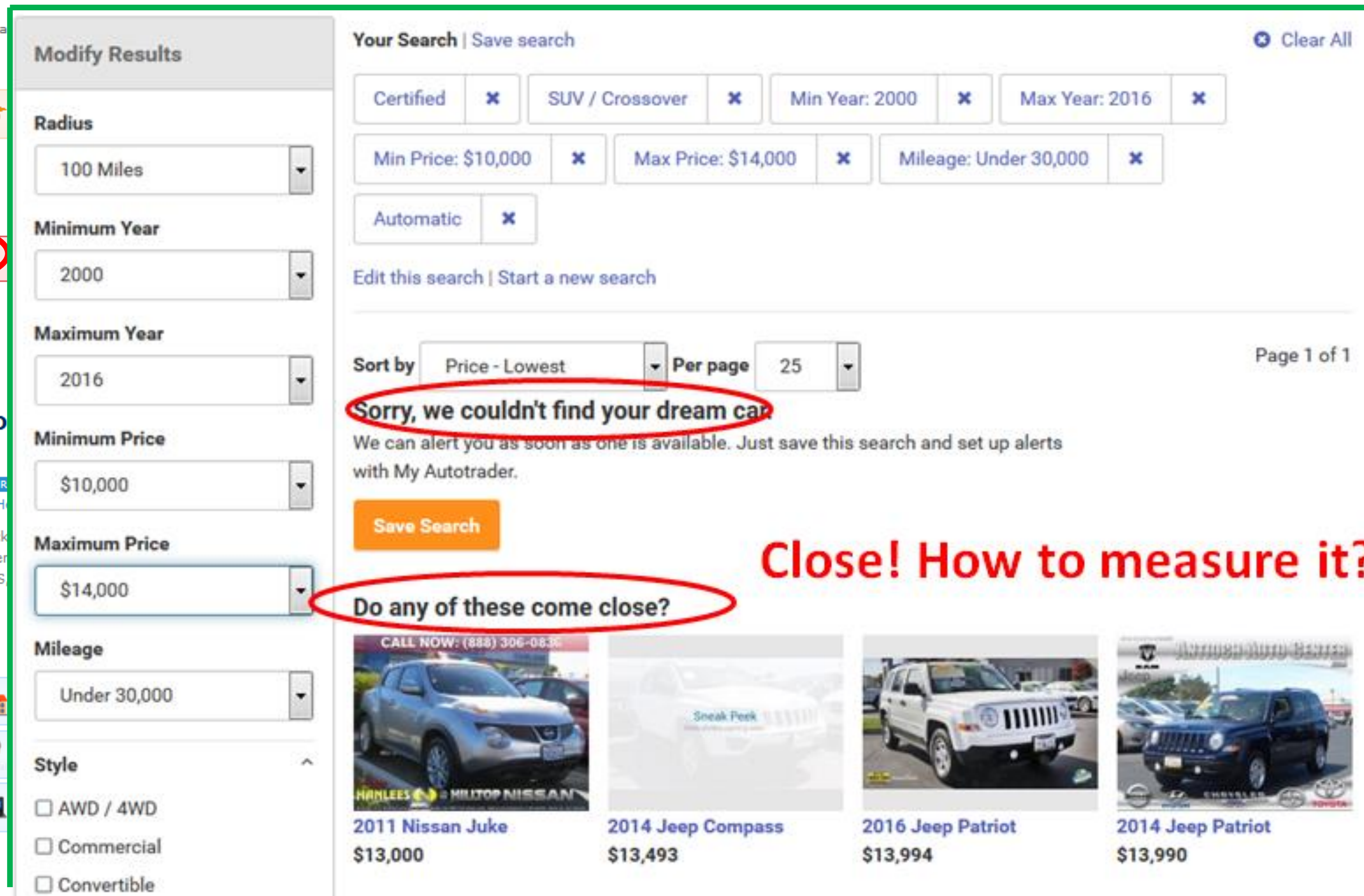
remaining thirds Láďa Peška, KSI MFF UK

Outline of this part of lectures

- Substantially modified this year – this course follows on the NSWI166 (previous NDBX021, NDBI037 can be consulted)
- Motivation remains
  - User requirements (implicit/explicit) – possibly conflicting, multicriterial
  - (partly) linear models to enable lab paper solutions
- What is new
  - building a larger portfolio of aggregation models for testing which fits better to user modelling (pure heuristic)
  - More emphasis to visual part …
- We begin with fast repetition of LMPM - Linear Monotone Preference Model + upgrade to 4D …
  - Data cube, Preference cube, contour lines, top-k, …
- First lab on paper solutions

Multicriterial conflicting requirements – No such product Do any of these come close?

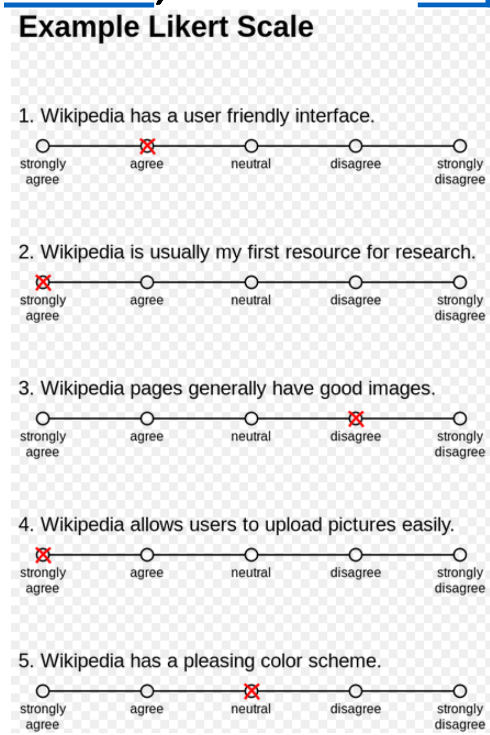


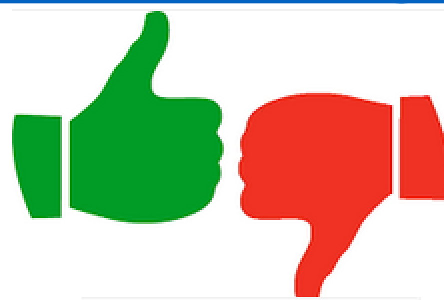


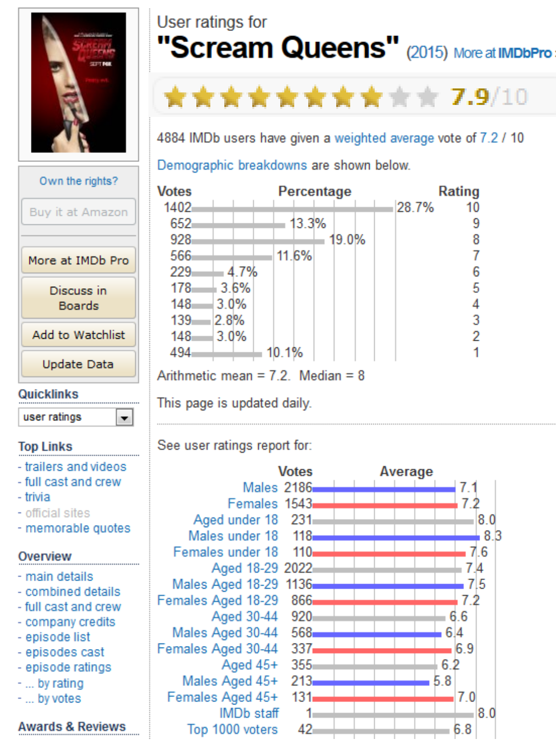
Close! How to measure it?

Preference – human, intuitive, ...scaled

- IT - more and more about the people and for the people
- Quality – in the language (good, better, best, bad, worse worst), we sense the visual stimuli in the environment – e.g., depth and motion - step-wise, psychology Likert's scale, we will **represent ordering by numbers** **(ratings)**







User ratings for
"Scream Queens" (2015) More at IMDbPro »

7.9/10

4884 IMDb users have given a weighted average vote of 7.2 / 10

Demographic breakdowns are shown below.

Votes	Percentage	Rating
1402	28.7%	10
652	13.3%	9
928	19.0%	8
566	11.6%	7
229	4.7%	6
178	3.6%	5
148	3.0%	4
139	2.8%	3
148	3.0%	2
494	10.1%	1

Arithmetic mean = 7.2. Median = 8

This page is updated daily.

See user ratings report for:

	Votes	Average
Males	2186	7.1
Females	1543	7.2
Aged under 18	231	8.0
Males under 18	118	8.3
Females under 18	110	7.6
Aged 18-29	2022	7.4
Males Aged 18-29	1136	7.5
Females Aged 18-29	866	7.2
Aged 30-44	920	6.6
Males Aged 30-44	568	6.4
Females Aged 30-44	337	6.9
Aged 45+	355	6.2
Males Aged 45+	213	5.8
Females Aged 45+	131	7.0
IMDb staff	1	8.0
Top 1000 voters	42	6.8

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Overview
- main details
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- full cast and crew
- company credits
- episode list
- episodes cast
- episode ratings
- ... by rating
- ... by votes

Awards & Reviews

Decathlon data – scale-points, multicriterial

P	Athlete	Points		P	100m	P	Long	P	Shot	P	High	P	400m	P	110mh	P	Discus	P	Pole	P	Javelin	P	1500m
1	Šebrle CZE	9026		1	10,64	1	8.11	4	15.93	1	2.12	2	46,89	1	13,92	4	48.53	2	5.3	1	70.16	5	4.21,85
2	Nool EST	8604		4	10,66	2	7.8	3	15.83	5	2.12	8	47,70	3	13,99	1	47.92	4	5.2	6	68.15	1	4.21,98
3	Dvorak CZE	8527		2	10,73	3	7.69	9	15.67	7	2.06	1	47,79	4	14,22	3	46.74	11	5.1	2	66.94	12	4.26,13
4	Lobodin RUS	8465		17	10,76	8	7.49	1	15.33	12	2.03	9	48,01	7	14,30	5	46.73	10	5	3	66.66	10	4.27,65
5	Zsivoczky HUN	8173		3	10,84	6	7.39	8	15.16	4	2	14	48,67	10	14,30	7	46.61	12	5	14	63.93	11	4.31,69
6	Ambrosch AUT	8122		10	10,87	11	7.35	16	15.1	13	2	3	48,76	9	14,36	9	46.41	9	4.9	15	61.65	3	4.33,58
7	Kürtösi HUN	8099		14	10,89	4	7.32	10	14.85	2	1.97	17	48,76	2	14,46	11	44.07	1	4.8	5	60.57	4	4.35,97
8	Warners NED	8085		8	10,90	5	7.19	7	14.77	3	1.97	10	48,77	8	14,48	2	43.32	6	4.8	16	59.97	6	4.36,36
9	Hämäläinen FIN	8028		6	10,93	12	7.17	6	14.71	14	1.97	5	48,81	6	14,56	8	41.64	8	4.8	7	59.83	2	4.39,11
10	Jensen NOR	8004		9	10,99	7	7.16	17	14.67	15	1.97	4	48,91	12	14,61	12	41.56	3	4.7	10	58.51	16	4.40,22
11	Schönbeck GER	7891		13	10,99	9	7.11	5	14.6	6	1.94	7	49,07	14	14,70	15	41.3	7	4.7	17	58.23	8	4.42,47
12	Niklaus GER	7891		5	11,01	13	7.11	2	14.37	8	1.94	13	49,26	15	14,83	14	41.14	15	4.6	11	58.11	9	4.42,66
13	Tebbich AUT	7632		16	11,03	10	6.94	11	14.17	16	1.94	6	49,33	17	14,97	10	40.38	5	4.5	8	55.62	13	4.46,57
14	Llanos PUR	7613		7	11,08	15	6.93	13	13.78	9	1.91	16	49,90	11	15,06	13	40.18	13	4.5	4	54.56	15	4.47,22
15	SchnallingerAUT	7576		12	11,09	14	6.89	14	13.67	11	1.88	12	50,14	13	15,07	6	39.52	17	4.4	13	54.32	17	4.48,52
16	Walser AUT	7546		11	11,31	17	6.83	12	12.99	10	1.85	15	50,25	16	15,27	16	39.45	16	4.2	12	51.95	7	4.49,58
17	Walser AUT	7506		15	11,35	16	6.81	15	12.98	17	1.82	11	50,51	5	15,43	17	37.2	14	4.1	9	50.33	14	4.59,38

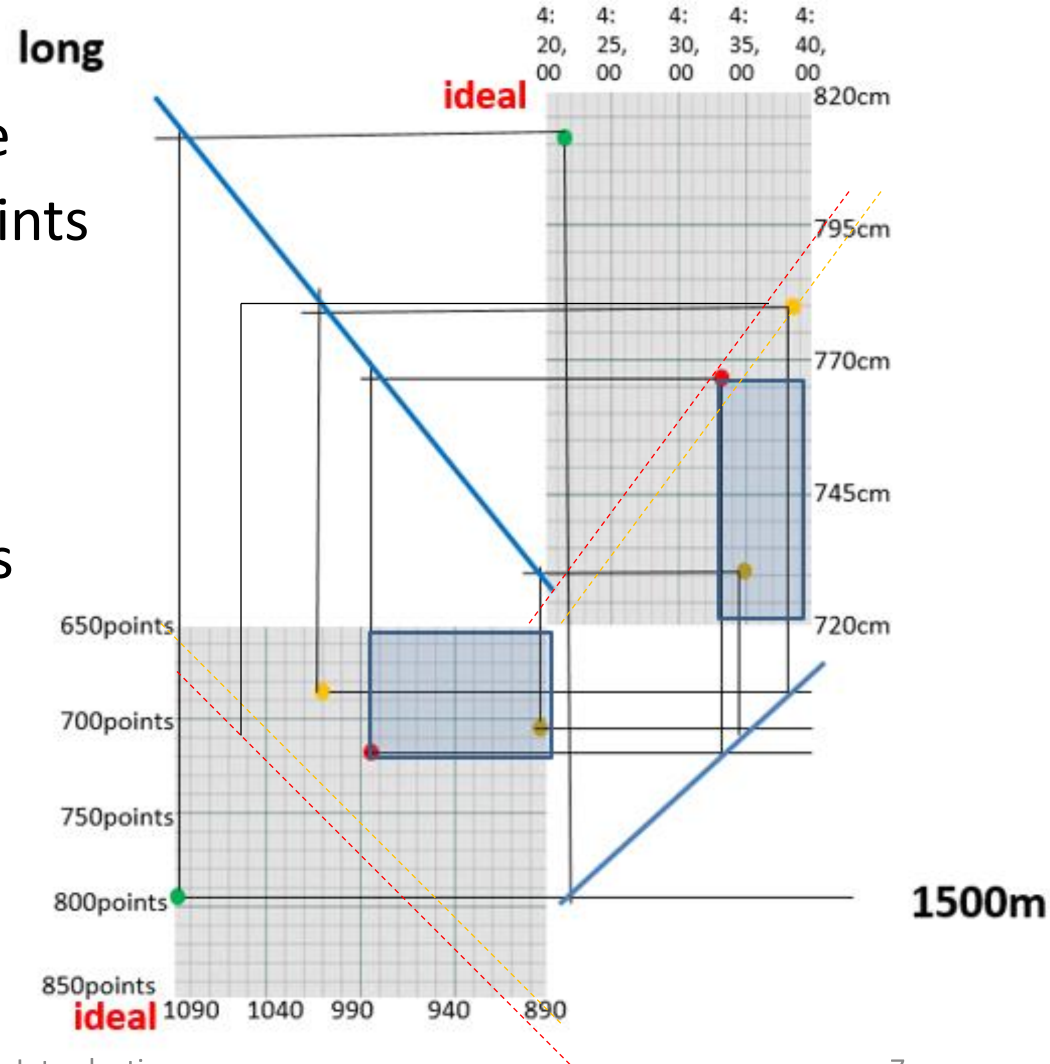
Decathlon points-commeasurable

P	Athlete	Points	P	100m	P	Long	P	Shot	P	High	P	400m	P	110mh	P	Discus	P	Pole	P	Javelin	P	1500m
1	Šebrle CZE	9026	1	942	1	1089	4	847	1	915	2	964	1	985	4	840	2	1004	1	892	5	799
2	Nool EST	8604	4	938	2	1010	3	841	5	915	8	924	3	976	1	827	4	972	6	861	1	798
3	Dvorak CZE	8527	2	922	3	982	9	831	7	859	1	919	4	946	3	803	11	941	2	843	12	770
4	Lobodin RUS	8465	17	915	8	932	1	810	12	831	9	909	7	936	5	803	10	910	3	839	10	760
5	Zsivoczky HUN	8173	3	897	6	908	8	800	4	803	14	877	10	936	7	800	12	910	14	797	11	734
6	Ambrosch AUT	8122	10	890	11	898	16	796	13	803	3	873	9	929	9	796	9	880	15	763	3	721
7	Kürtösi HUN	8099	14	885	4	891	10	780	2	776	17	873	2	916	11	748	1	849	5	746	4	706
8	Warners NED	8085	8	883	5	859	7	776	3	776	10	872	8	913	2	732	6	849	16	737	6	703
9	Hämäläinen FIN	8028	6	876	12	854	6	772	14	776	5	870	6	903	8	698	8	849	7	735	2	686
10	Jensen NOR	8004	9	863	7	853	17	769	15	776	4	866	12	897	12	696	3	819	10	715	16	679
11	Schönbeck GER	7891	13	863	9	840	5	765	6	749	7	858	14	886	15	691	7	819	17	711	8	665
12	Niklaus GER	7891	5	858	13	840	2	751	8	749	13	849	15	870	14	688	15	790	11	709	9	664
13	Tebbich AUT	7632	16	854	10	799	11	739	16	749	6	846	17	853	10	672	5	760	8	672	13	640
14	Llanos PUR	7613	7	843	15	797	13	715	9	723	16	819	11	842	13	668	13	760	4	656	15	636
15	Schnallinger AUT	7576	12	841	14	788	14	708	11	696	12	808	13	841	6	655	17	731	13	653	17	628
16	Walser AUT	7546	11	793	17	774	12	667	10	670	15	803	16	817	16	653	16	673	12	617	7	621
17	Walser AUT	7506	15	784	16	769	15	666	17	644	11	791	5	798	17	608	14	645	9	593	14	563

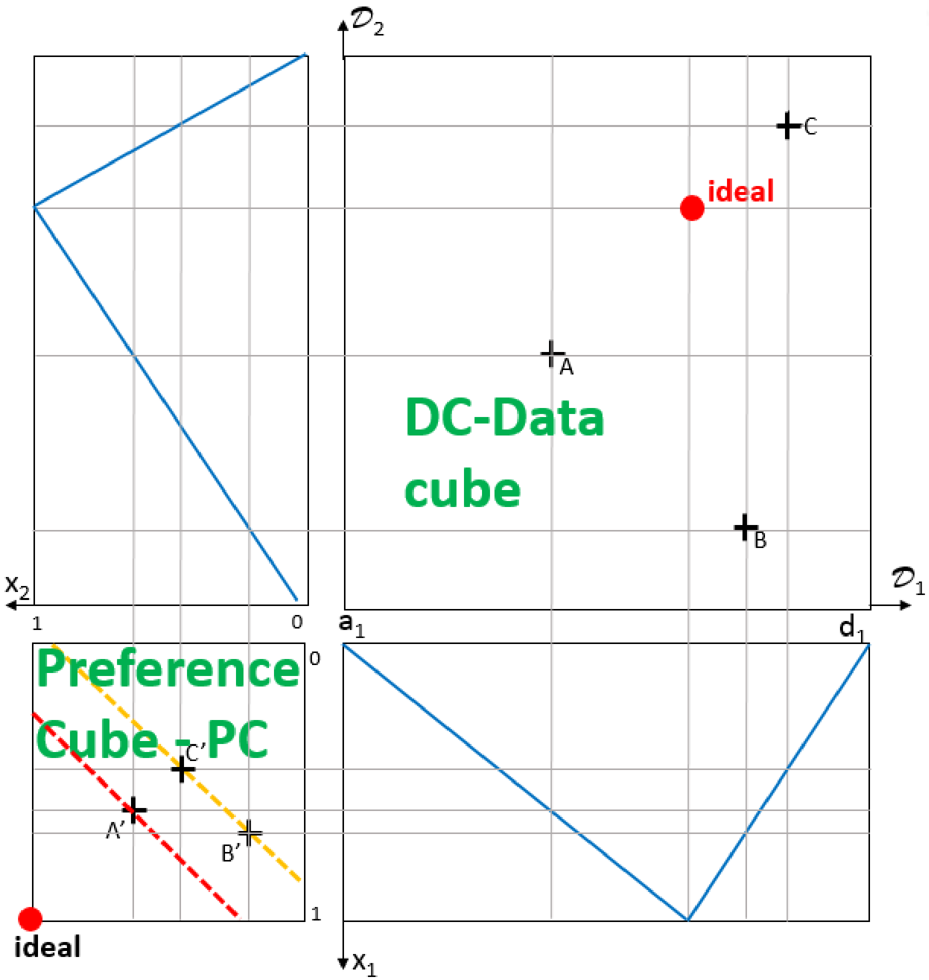
Sum of points makes Decathlon linear

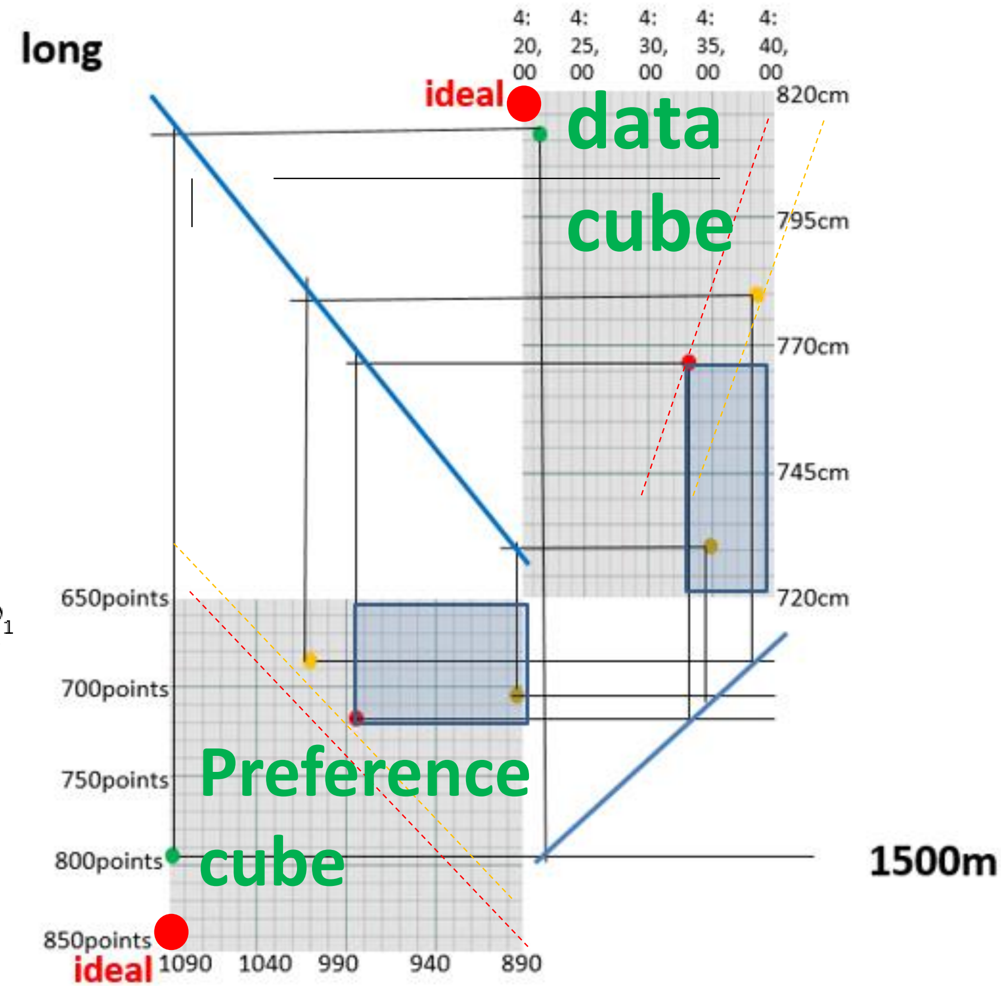
P	Athlete	Points
1	Šebrle CZE	9026
2	Nool EST	8604
3	Dvorak CZE	8527
4	Lobodin RUS	8465

- Data cube (upper right) – **point function** transforms achievements to preference cube (lower left)
- • dominates •
- • and • are incomparable
- Sum (aggregation) of points in these two events
  - • = 1703 points
  - • = 1696 points
- PC contour line connects points with same result in Pareto cube
- Contour line can be propagated to data cube



Decathlon like preference model = analogy for information ordering in web e-shops





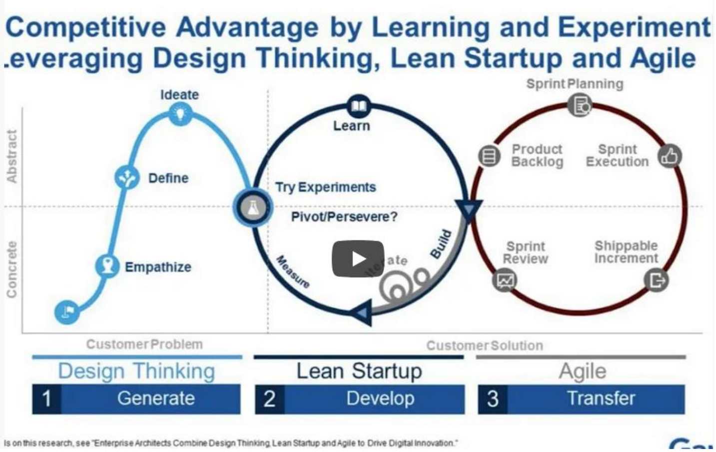
Linear **Monotone** Preference Model-LMPM

- Decathlon – "**single user**" **IAAF** rules order athletes
  - Disciplines $\mathcal{A}_1,\dots,\mathcal{A}_{10}$; domains $\mathcal{D}_1,\dots,\mathcal{D}_{10}$; ideal (field / track)
  - $\mathcal{A}_i$ point function $\mathbf{f_i} : \mathcal{D}_i \rightarrow N$ makes results commeasurable
    - Winner - overall IAAF achievement is obtained via sum
      $\Sigma\{\mathbf{f_i}\,(\text{athleteID}.\mathcal{A}_i): i = 1, \dots, 10\}$
- Retail, e-shop – **set of users U**, $\text{LMPM}^{\mathbf{u}}$ orders items
  - Attributes $\mathcal{A}_1,\dots,\mathcal{A}_m$; domains $\mathcal{D}_1,\dots,\mathcal{D}_m$; ideal points can be for each user different
  - Degree of preference for $\mathcal{A}_i$ and user $\mathbf{u} \in U$ $\mathbf{f_i^u}: \mathcal{D}_i \rightarrow [0, 1]$ – hardly made commeasurable in response time
    - Winner, top-k, overall degree of preference - aggregation
      $r^{f,t}(\text{objectID}) = \mathbf{t^u}\{\mathbf{f_i^u}\,(\text{objectID}.\mathcal{A}_i): i = 1, \dots, m\}$

Here $\mathbf{t^u}: [0, 1]^m \rightarrow [0, 1]$, $\mathbf{t^u}(0,\dots,0) = 0$, $\mathbf{t^u}(1,\dots,1) = 1$,
$\mathbf{t^u}$ **monotone**(linear) - preserves Pareto ordering,

Who, what, when, where, why

- **Design thinking** - is a term used to represent a set of cognitive, strategic and practical processes by which design concepts - is also associated with prescriptions for the **innovation** of products and services within business and social contexts
- **Lean start up** - is a methodology for developing businesses and products that aims to shorten product development cycles and rapidly discover if a proposed business model is viable; this is achieved by adopting a combination of business-hypothesis-driven experimentation, iterative (β)product releases, and validated learning
- Lean Startup Meets Design Thinking
- Three-legged stool: Design Thinking, Lean Startup, Agile
- B2B/B2C, **our** story, use-case, dream, running example
- (partly) linear models to enable lab paper solutions

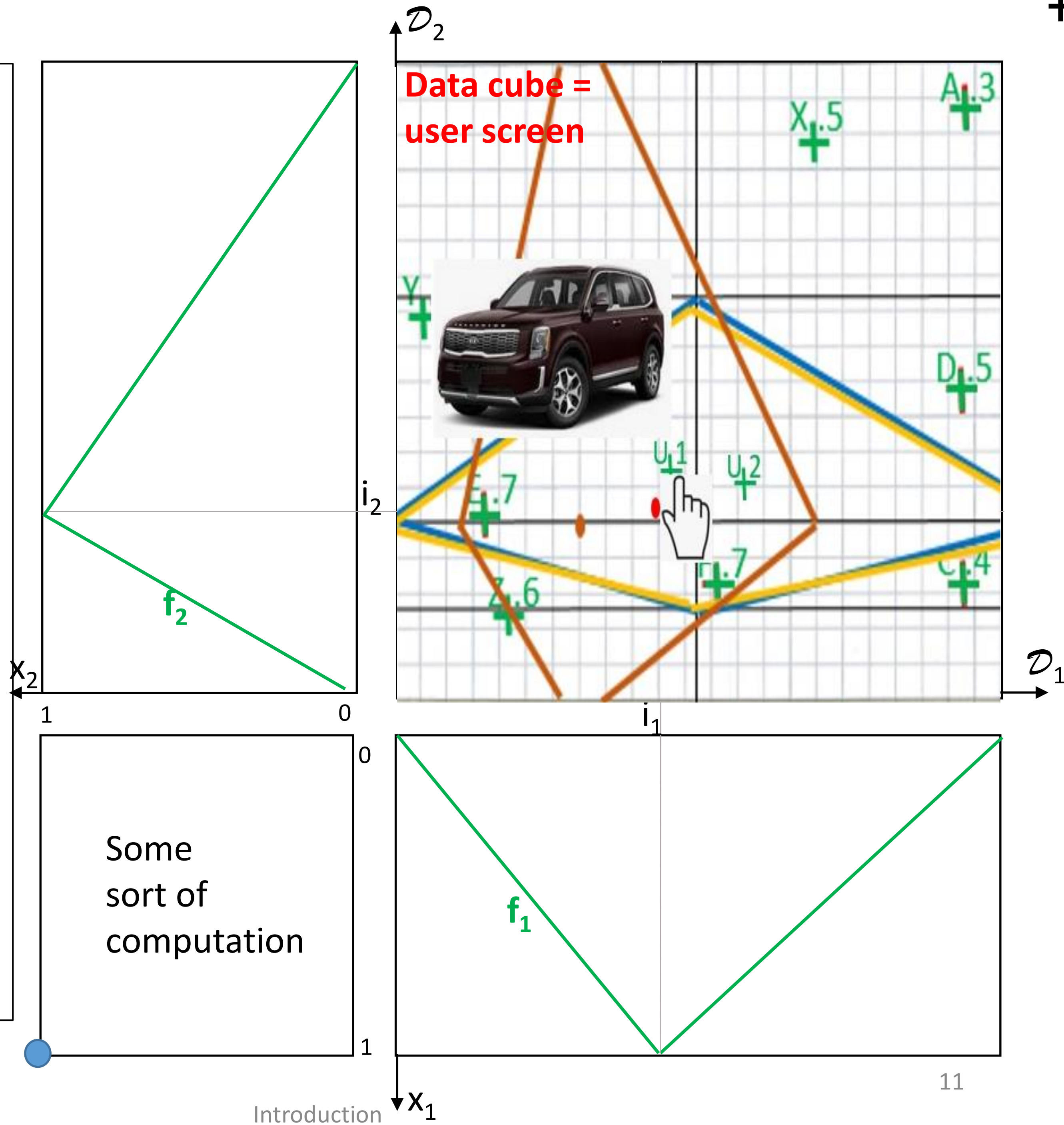


Dream – Data cube = user screen

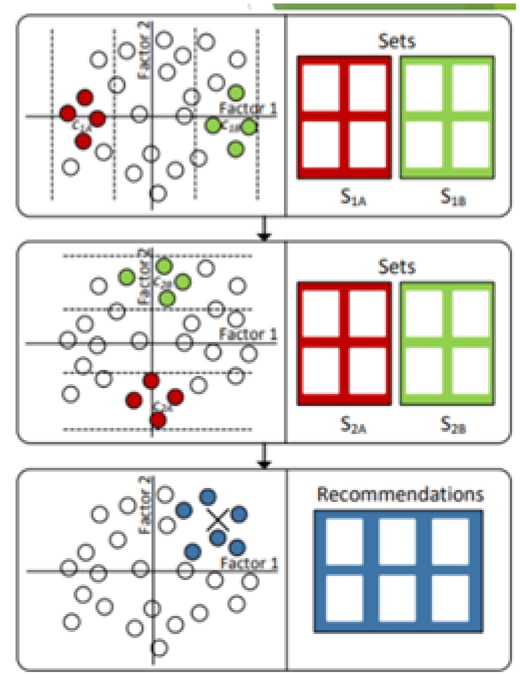
Let us build LMPM step by step

Data model: attributes
- Either known $\mathcal{A}_1$, $\mathcal{A}_2$; domains $\mathcal{D}_1$, $\mathcal{D}_2$;
- Or latent

Triangular (trapezoidal) degree of preference of $\mathcal{A}_j$, a value from $\mathcal{D}_j$ (local preference) is given by an ideal point i_j and function f_j (can have also different shape)



Visual dimensionality reduction

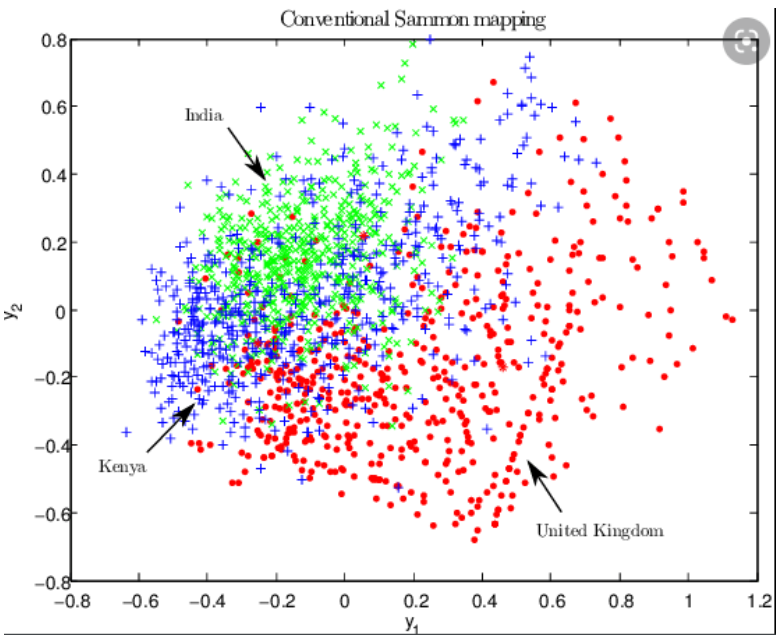


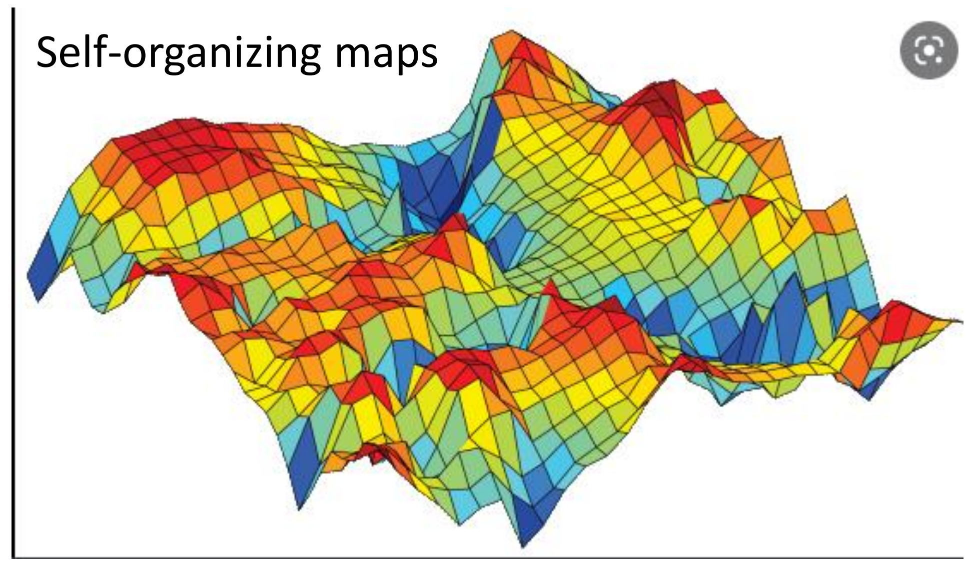
Our eyes process global visual information more easily

- Keeps similar objects close, dimensionality reduction
- Sammon mapping, Kohonen self-organizing map, latent factors, … 2D/3D axes do not have real meaning

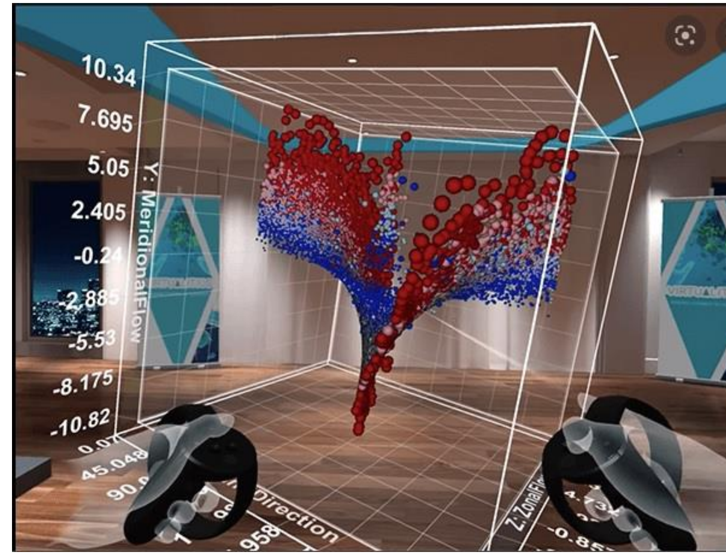
Peska-Lokoc. Rating-aware self-organizing maps, MMM, oriented to VBS competition (prominent display areas, so the most relevant results should be mapped there).

Do users prefer visual information by triangle-rule (F-rule, Z-rule, …), there is a room for eye-tracking user experiments?





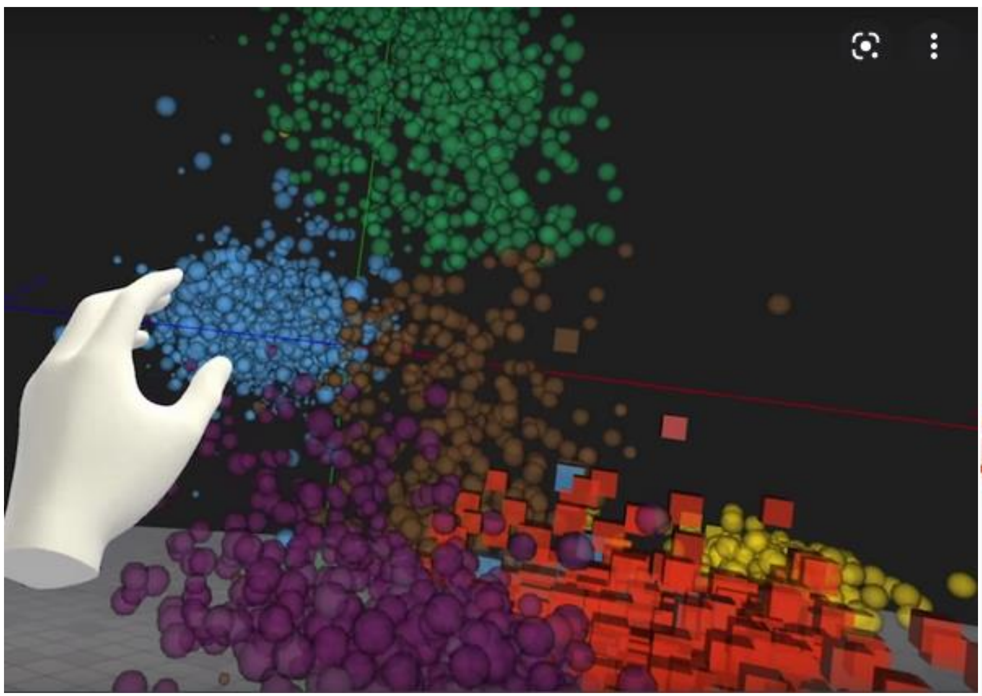
Augmented/virtual reality

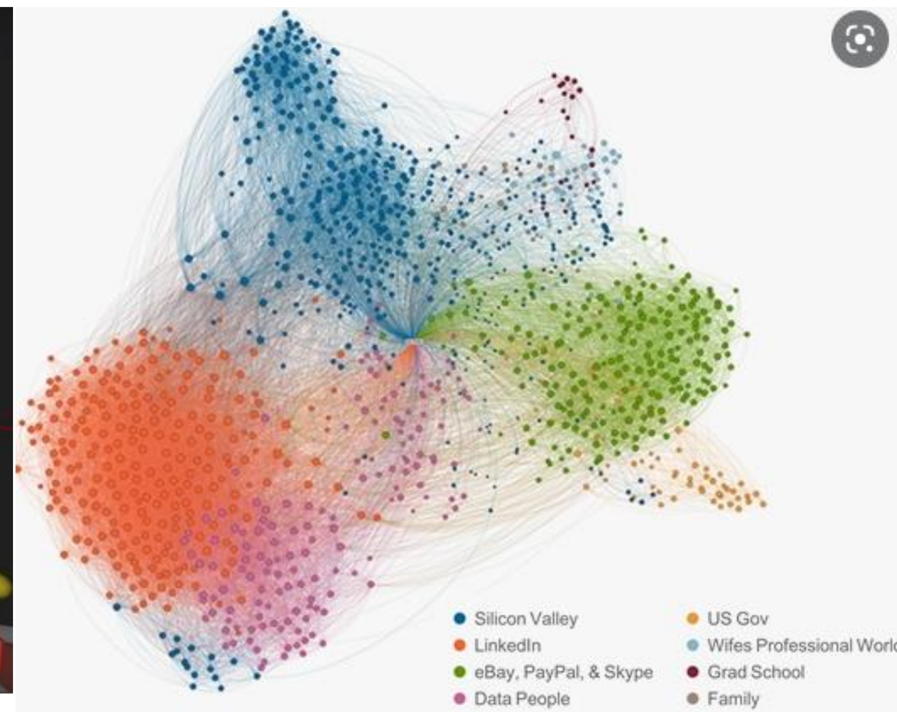


True attributes represented by 2D/3D position, color, size, shape (cube, ball), transparency, glittering

- human can percept more than 7-8 dimensions
- You need to wear AR/VR glasses

….





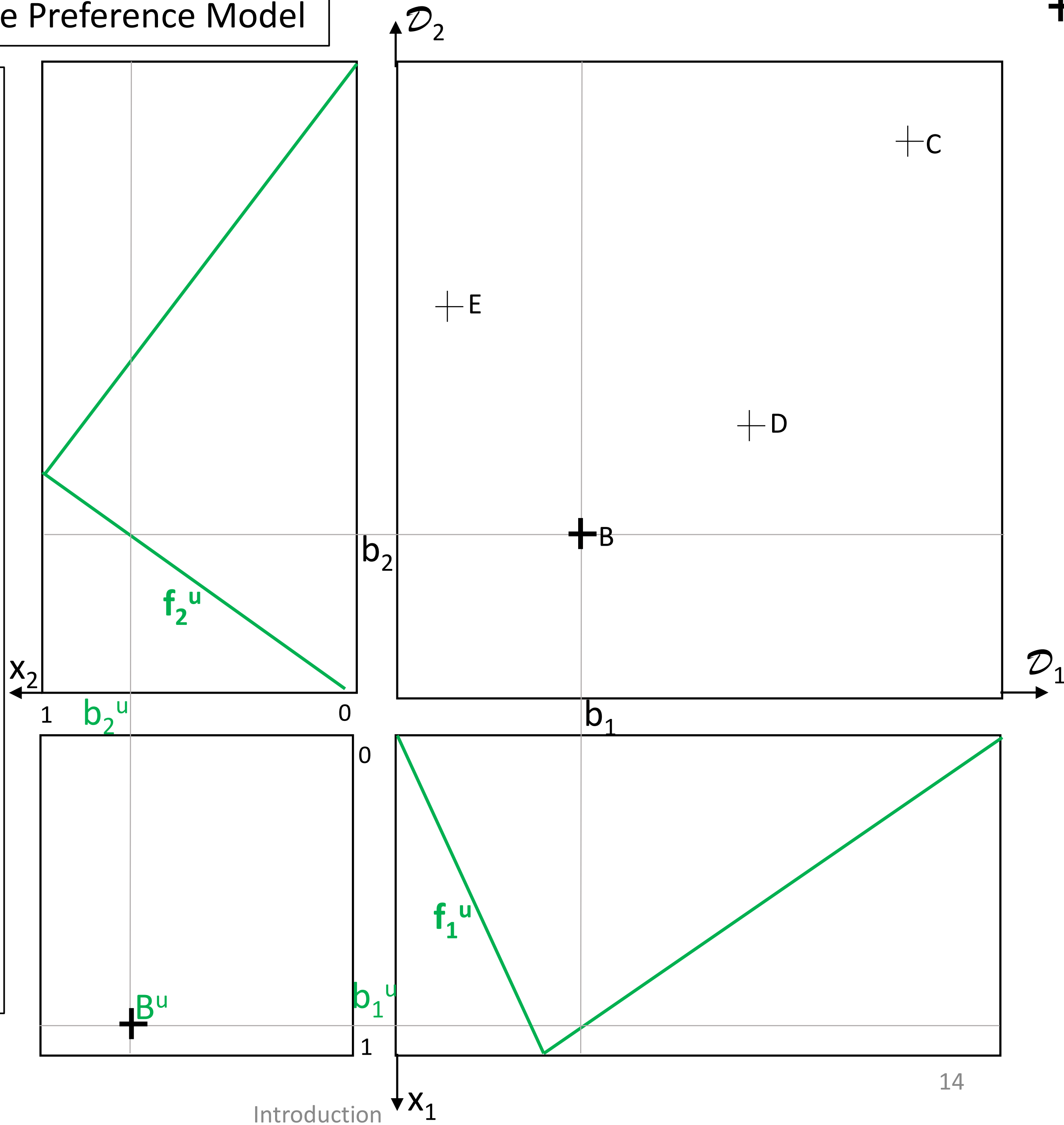
LMPM – Linear Monotone Preference Model

Let us describe steps leading to calculation of preference degree of item B (for user u), we first describe mapping DC-data cube to PC-preference cube

Assume degree of attribute preference $f_i^u: \mathcal{D}_i \rightarrow [0, 1]$,

Object with objectID = B has attribute values $B.\mathcal{A}_1 = b_1$ and $B.\mathcal{A}_2 = b_2$, sometimes we write $B=(b_1, b_2)$.

Attribute preference degrees $f_j^u(B.\mathcal{A}_j) = b_j^u$ and corresponding point in preference cube is $B^u = (b_1^u, b_2^u)$, similarly C, D,...



Note, that point B^u has 4 coimages B, B', B'', B'''

Degree of preference for user $u \in U$ are given by f_1^u and f_2^u .

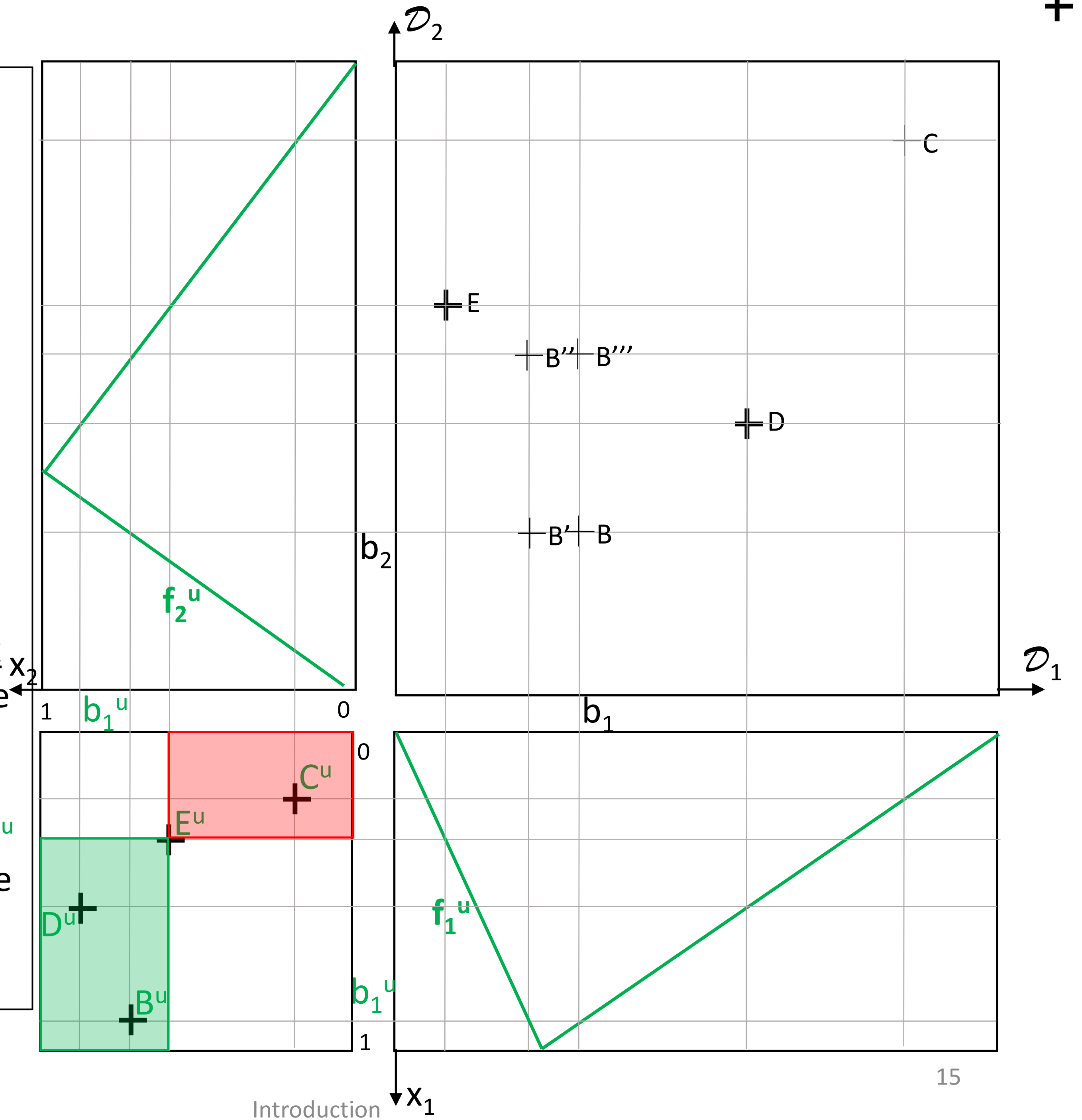
Note that both D^u and B^u are in both attributes better than E^u , B^u and D^u are incomparable, define Pareto ordering of pref. cube $(\underline{x}) <_{Pareto} (\underline{y})$ iff (for each i) $x_i \leq y_i$ & $(\exists i)\ x_i < y_i$,

We say that $\underline{y}$ dominates $\underline{x}$

Item E^u dominates whole red area and is dominated by whole green area

$<_{Pareto}$ is not linear, e.g. B^u and D^u are not comparable

Items in white areas are incomparable with E^u



Combining queries, requirements, services,

Combining = aggregating ratings (numbers in [0, 1])

User's requirements are also called criteria. Our typical problem is multicriterial (differs from multicriterial optimization).

Display size: from 14 " to 17.3 " ×

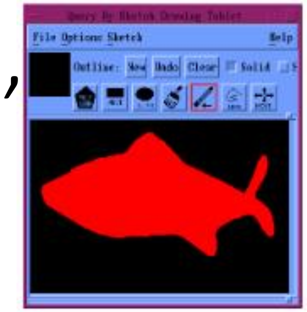
Size of operational RAM: from 8 GB to 32 GB ×

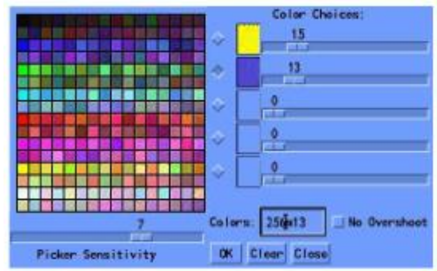
Storage capacity: from 1,500 GB to 2,000,000 GB ×

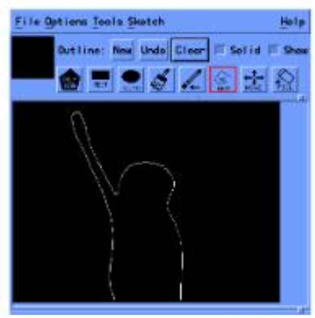
Certified × | SUV / Crossover × | Min Year: 2000 × | Max Year: 2016 ×

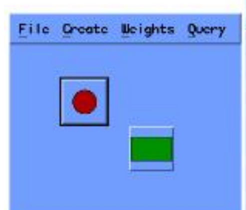
Min Price: $10,000 × | Max Price: $14,000 × | Mileage: Under 30,000 ×

Automatic ×





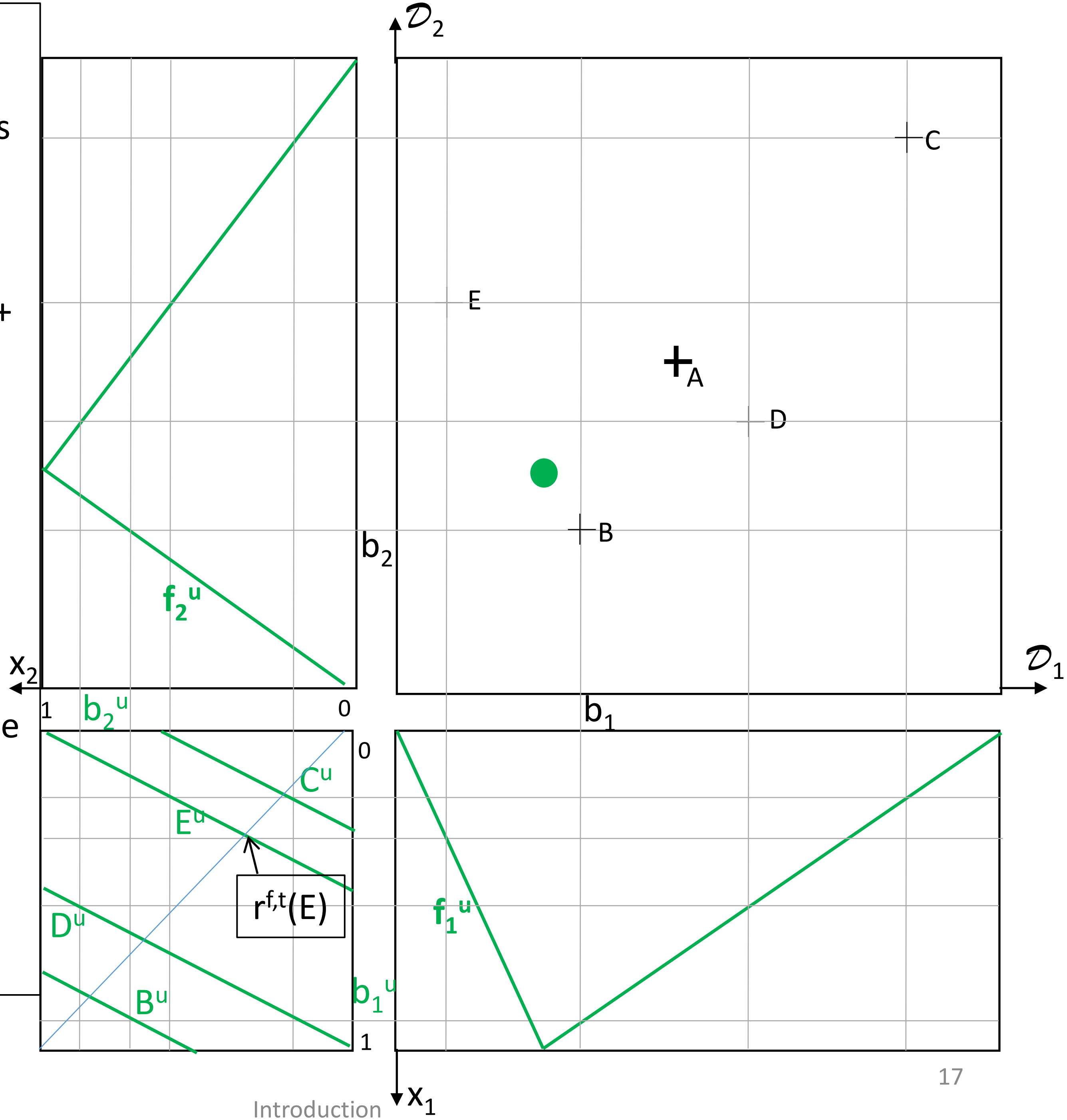




To get global preference degree of items we need aggregation functions. It is a function $[0,1]^2 \rightarrow [0,1]$ $t(x_1, x_2) = w_1 * x_1 + w_2 * x_2$, where $w_1, w_2 \geq 0$ are attribute weights with $w_1 + w_2 = 1$

Graph of t is a 3D object. Intuition behind display of aggregation function are contour lines for user **u**

Note, that on the preference cube diagonal corresponding contour line cl_y of preference degree $y \in [0,1]$ intersect the diagonal at point (y, y), $w_1 * x + w_2 * x = y$ gives $x * (w_1 + w_2) = y$, i.e., $x = y$



Preference model of user $u_{f,t}$ on data cube

Function $R^{f,t}: \Pi D_i \rightarrow [0,1]$

$R^{f,t}(a_1, ..., a_m) = t([f_i(a_i) : i = 1, ..., m])$

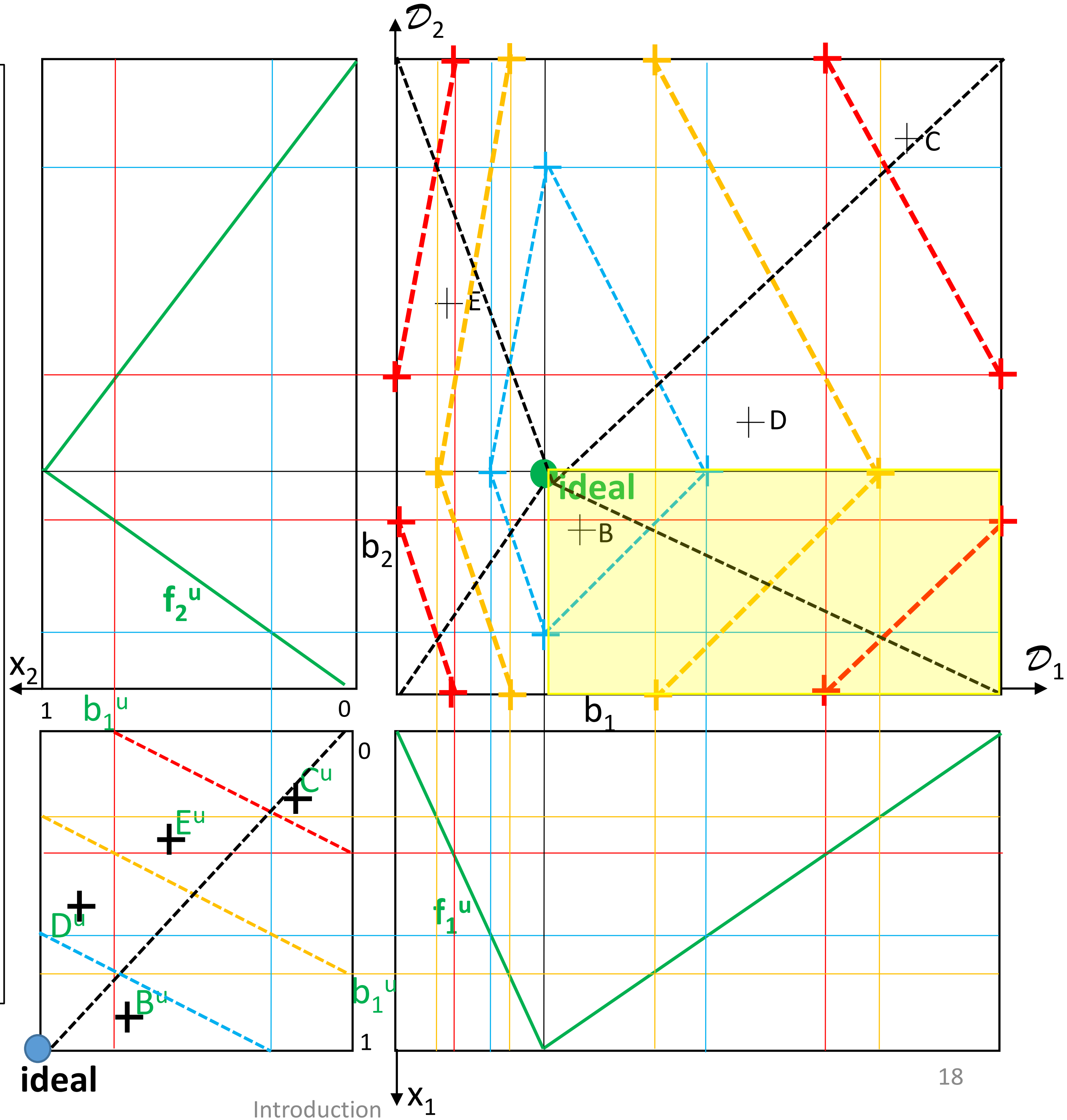
Ordering on data cube $(a_1, ..., a_m) \geq^{f,t} (b_1, ..., b_m)$ iff $R^{f,t}(a_1, ..., a_m) \geq R^{f,t}(b_1, ..., b_m)$ Odering can be vizualized as contour lines on ΠD_i

For better understanding are different contour lines (of same t) in colors

User $\mathbf{u_{f,t}}$, preference of user $u_{f,t}$, $R^{f,t}: \Pi D_i \rightarrow [0,1]$

$R^{f,t}(a_1, ..., a_m) = t([f_i(a_i) : i = 1, ..., m])$

$(a) \geq^{f,t} (\underline{b})$ iff $R^{f,t}(\underline{a}) \geq R^{f,t}(\underline{b})$



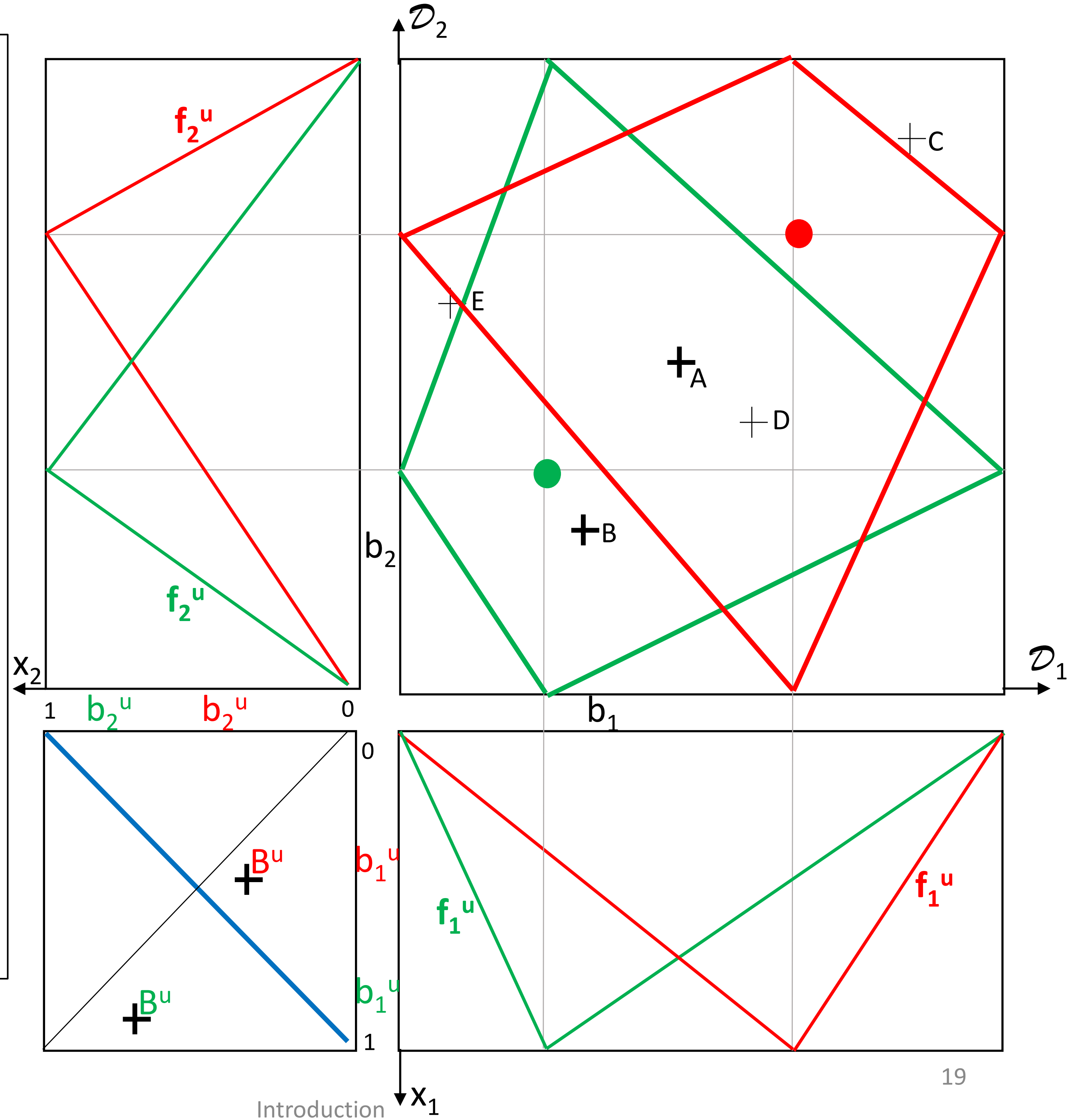
Data model: attributes $\mathcal{A}_1, \mathcal{A}_2$; domains $\mathcal{D}_1, \mathcal{D}_2$;

Ideal points can be for each user different, we consider users **u** and **u**. Both have same aggregation average AVG

As before we have $f_i^u: \mathcal{D}_i \rightarrow [0, 1]$ (for an user $u \in U$), so we have $\mathbf{f_i^u}$ and $\mathbf{f_i^u}$.

Object with objectID = B has attribute values $B.\mathcal{A}_1 = b_1$ and $B.\mathcal{A}_2 = b_2$, sometimes we write $B=(b_1, b_2)$ has two images in preference cube B^u and B^u .

Let us depict ½ contour line in DC



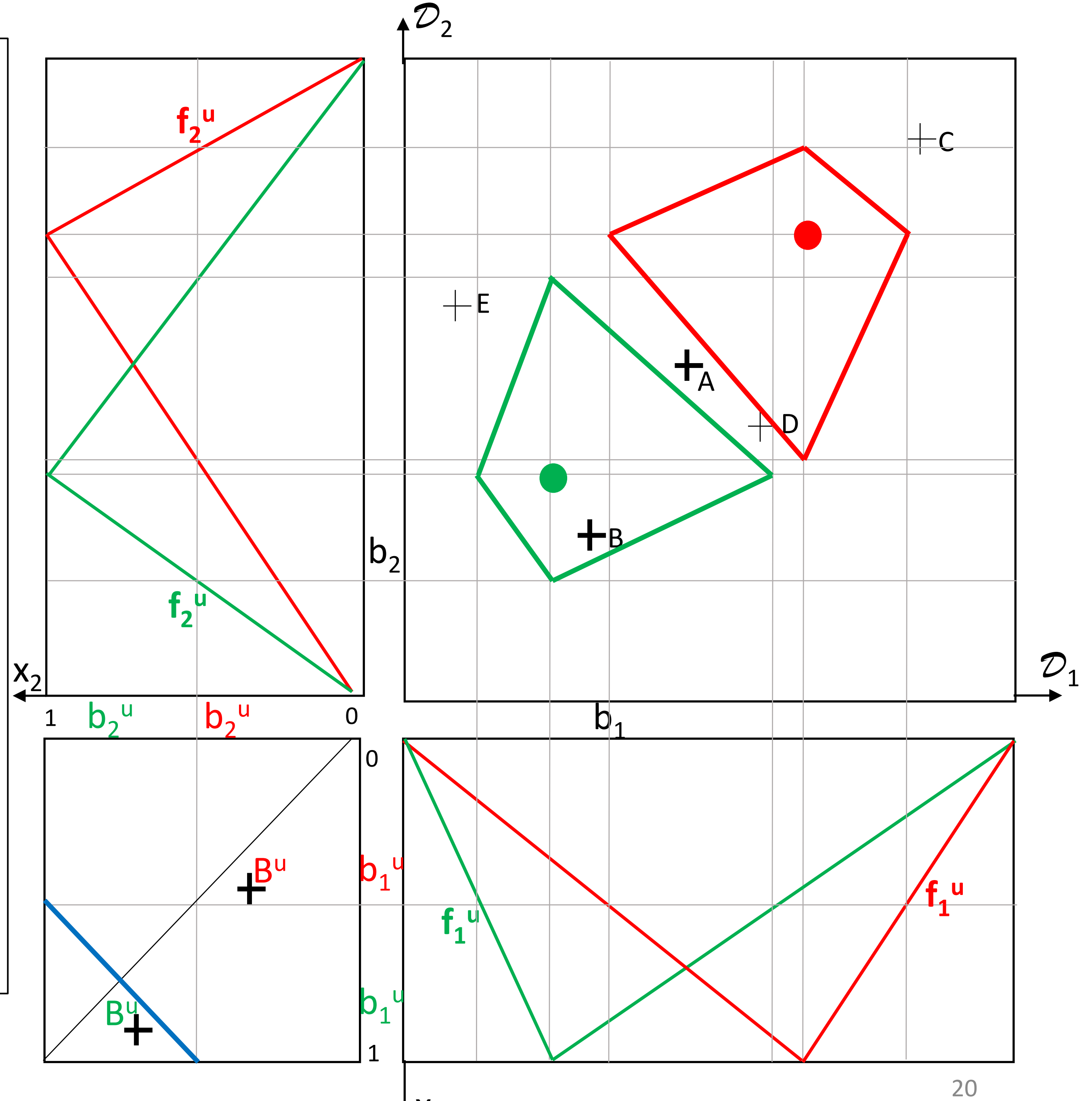
Data model: attributes $\mathcal{A}_1, \mathcal{A}_2$; domains $\mathcal{D}_1, \mathcal{D}_2$;

Ideal points can be for each user different, we consider users **u** and **u**. Both have same aggregation average AVG

As before we have $f_i^u: \mathcal{D}_i \rightarrow [0, 1]$ (for an user $u \in U$), so we have $\mathbf{f_i^u}$ and $\mathbf{f_i^u}$.

Object with objectID = B has attribute values $B.\mathcal{A}_1 = b_1$ and $B.\mathcal{A}_2 = b_2$, sometimes we write $B=(b_1, b_2)$ has two images in preference cube B^u and B^u .

Let us depict ¾ contour line in DC



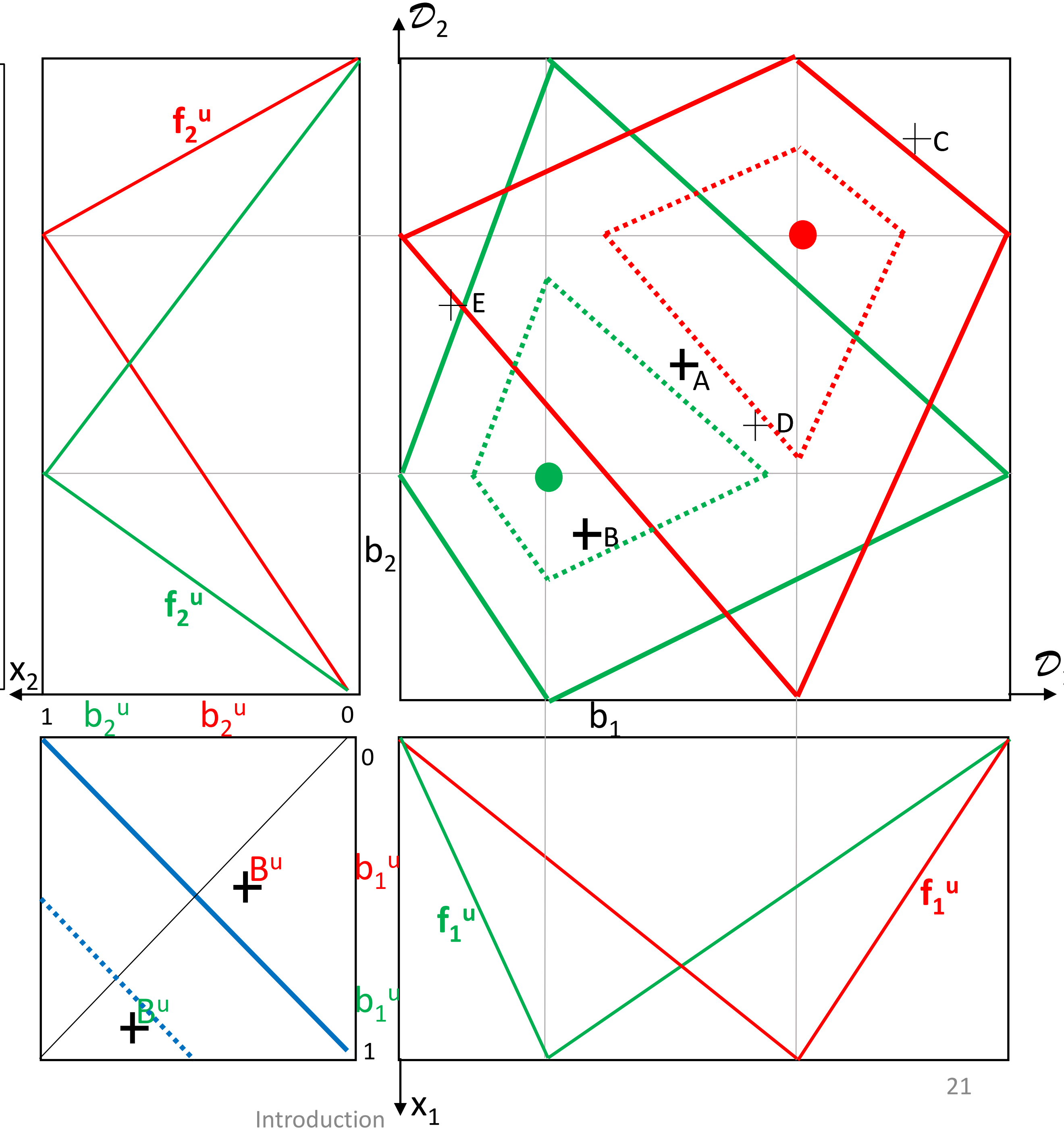
Previous two slides in one.

Observe ½ and ¾ contour lines in DC.

It seems that there is some parallelism.

Formulate statement, prove or disprove.

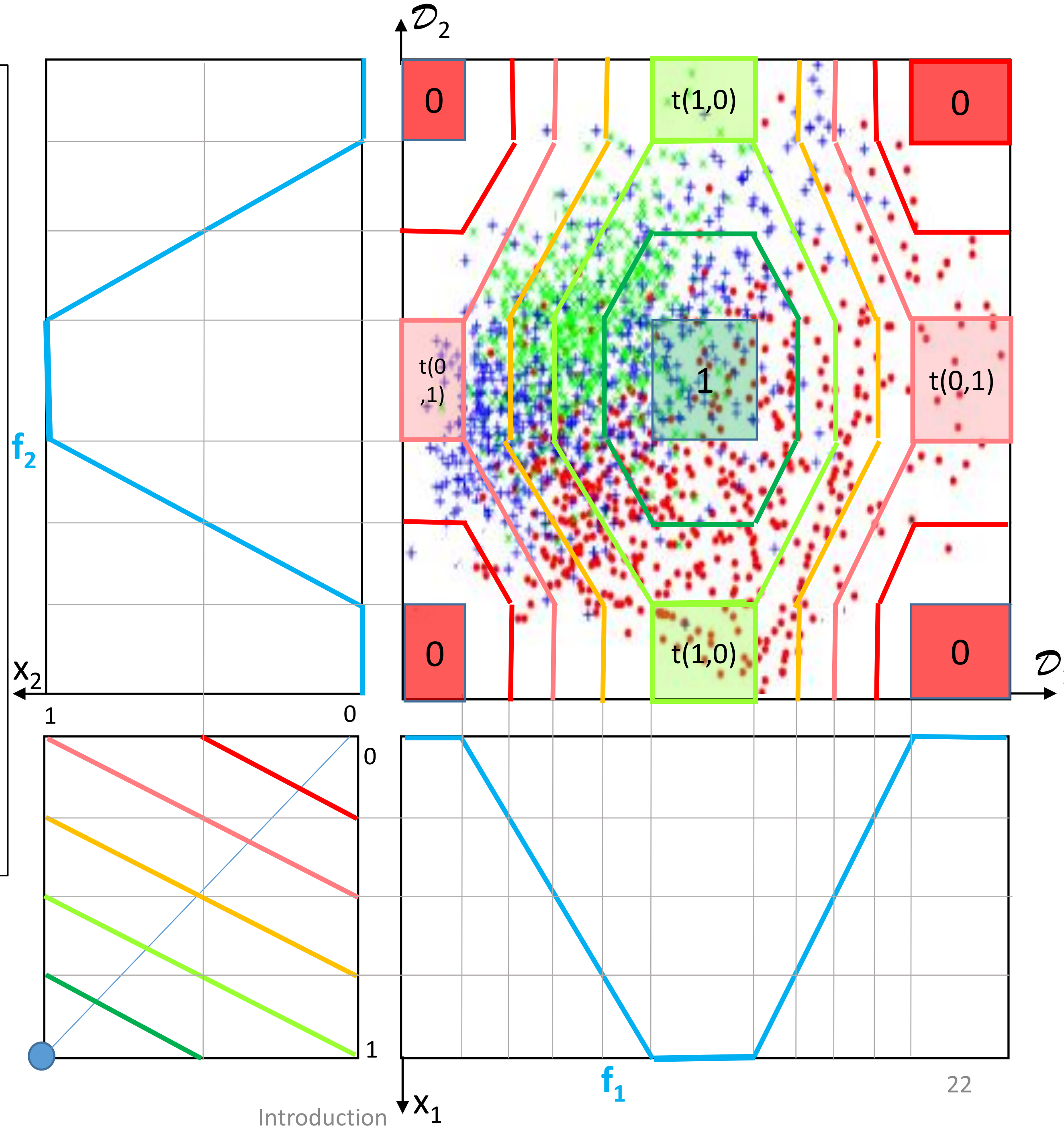
Interpret result, discuss intuitiveness



Trapezoidal degree of preference of $\mathcal{A}_j$, a value from $\mathcal{D}_j$ (local preference) is given by an ideal interval $[i_j^l, i_j^r]$ and analogically defined functions f_j (trapezoid is based on interval $[a_j, d_j]$

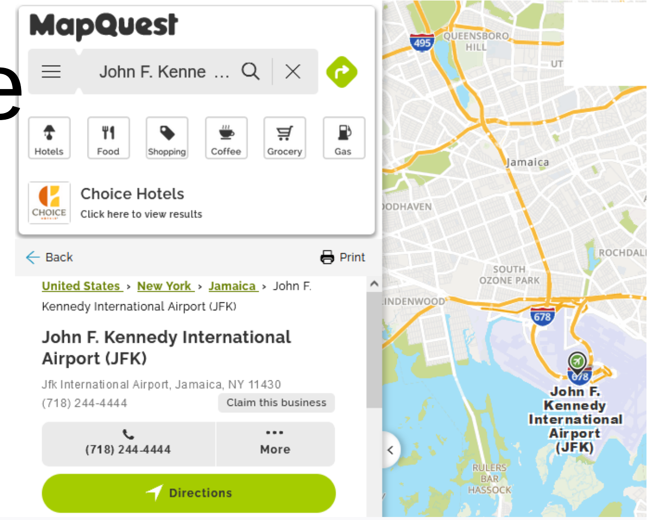
Consider different combination of “hill” “valley” shaped attribute preferences

Arbitrary point/line from DC/PC can be mapped to point/line in PC/DC

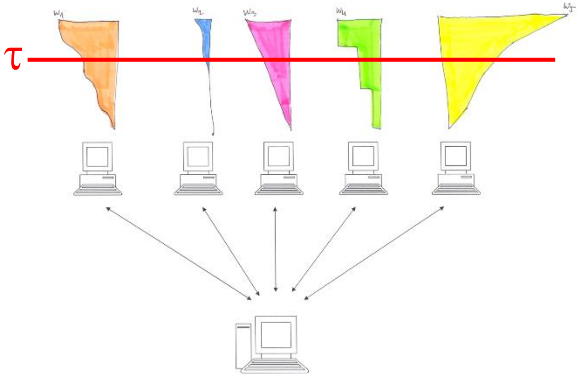


Web services – access mode – data types

- [*MapQuest*] returns the distance between two addresses.
- [*NYTimes Review*] gives the price range of a restaurant.
- [*Zagat*] gives a food rating to the restaurant.
- We follow paper [FLN] Fagin, Lotem, Naor, Optimal aggregation algorithms for middleware. Journal of Computer and System Sciences 66 (2003) 614–656 JCSS2003
  - Access mode – sorted, direct (random), stateless, …
  - From multimedia middleware (IBM Almaden Garlic project) top-k optimal querying to our multiuser LMPM



FLN threshold algorithm TA



1. **Do** sorted access in parallel to each of the
As an object R is seen under sorted access in some list, **do** random access to the other lists to find the grade x_j^R of object R in every list L_j. **Then** compute the grade $t(R) = t(x_1^R, ..., x_m^R)$ of object R.

If this grade is one of the k highest, we have seen, **then** remember object R and its grade t(R).

2. **For** each list L_i, let $\underline{x}_i$ be the grade of the last object seen under sorted access. **Define** the threshold value τ to be

$$\tau = t(\underline{x}_1, ..., \underline{x}_m)$$

As soon as at least k objects have been seen whose grade is at least equal to τ; **then** halt. **Else** go to **1**.

3. **Let** Y be a set containing the k objects that have been seen with the highest grades. The **output** is then the graded set $\{(R, t(R)) | R \in Y\}$ (ordered by t(R)).

FLN-TA graphically (2D)

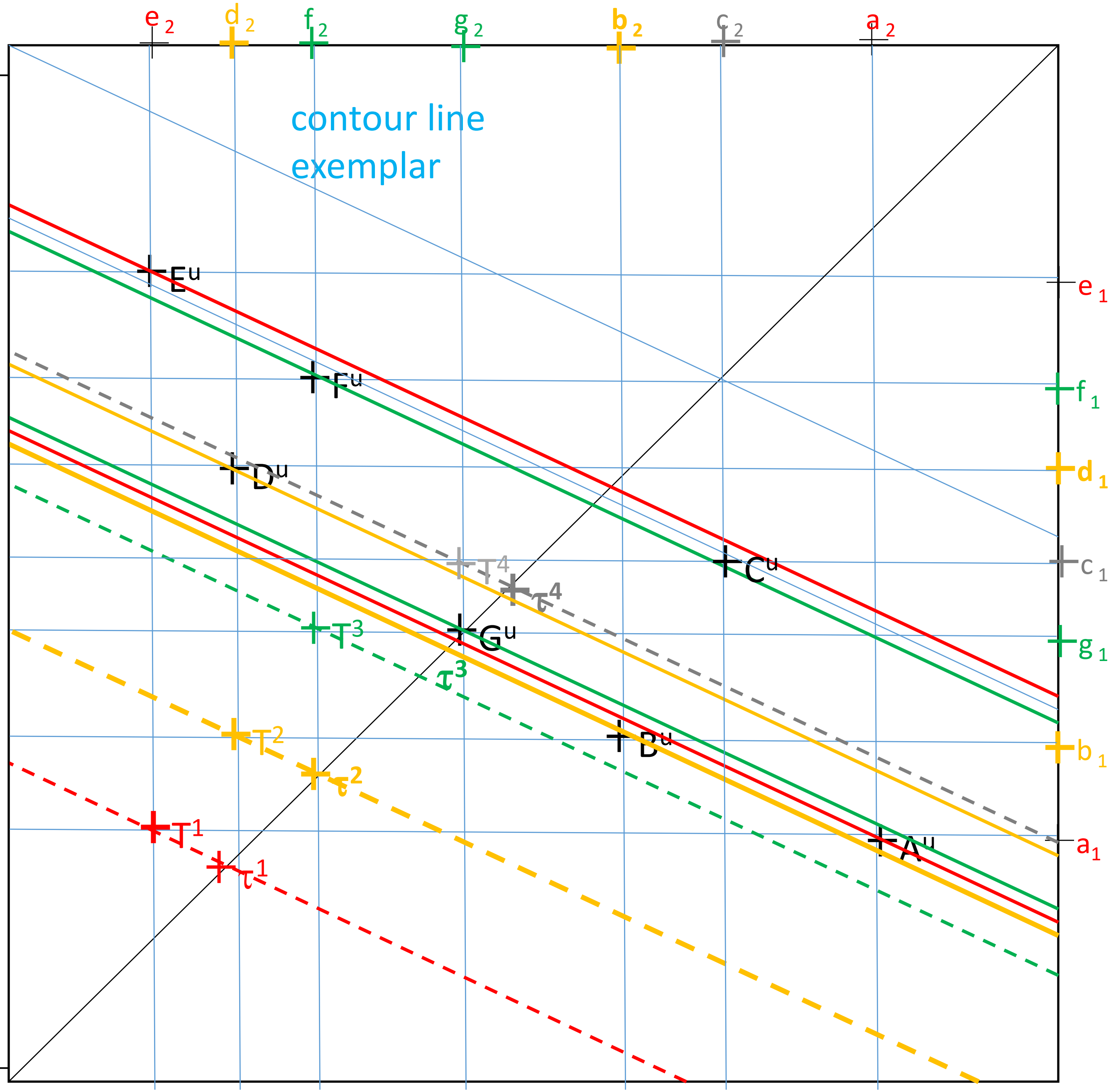
Big picture

In this case we need 4 steps to decide the winner

Certified order of items so far is B, A, G, D (for F, C, E we have to wait)

It seems that number of steps needed to decide the winner is at most n/2 + 1 where n is the # of items ($\lfloor n/2 \rfloor + 1$)

?can we find data distribution such that TA ends (decides winner / decides all) in arbitrary number of steps $s \leq (\lfloor n/2 \rfloor + 1)$?



FLN-TA graphically (4D)

In this [0,1]x[0,1] rectangle we see lists from FLN data model.

Horizontally are weights w_1=0.4, w_2=0.3 … (summed up to 1) and vertically preference degrees of objects (items) A, B, …, G in respective lists.

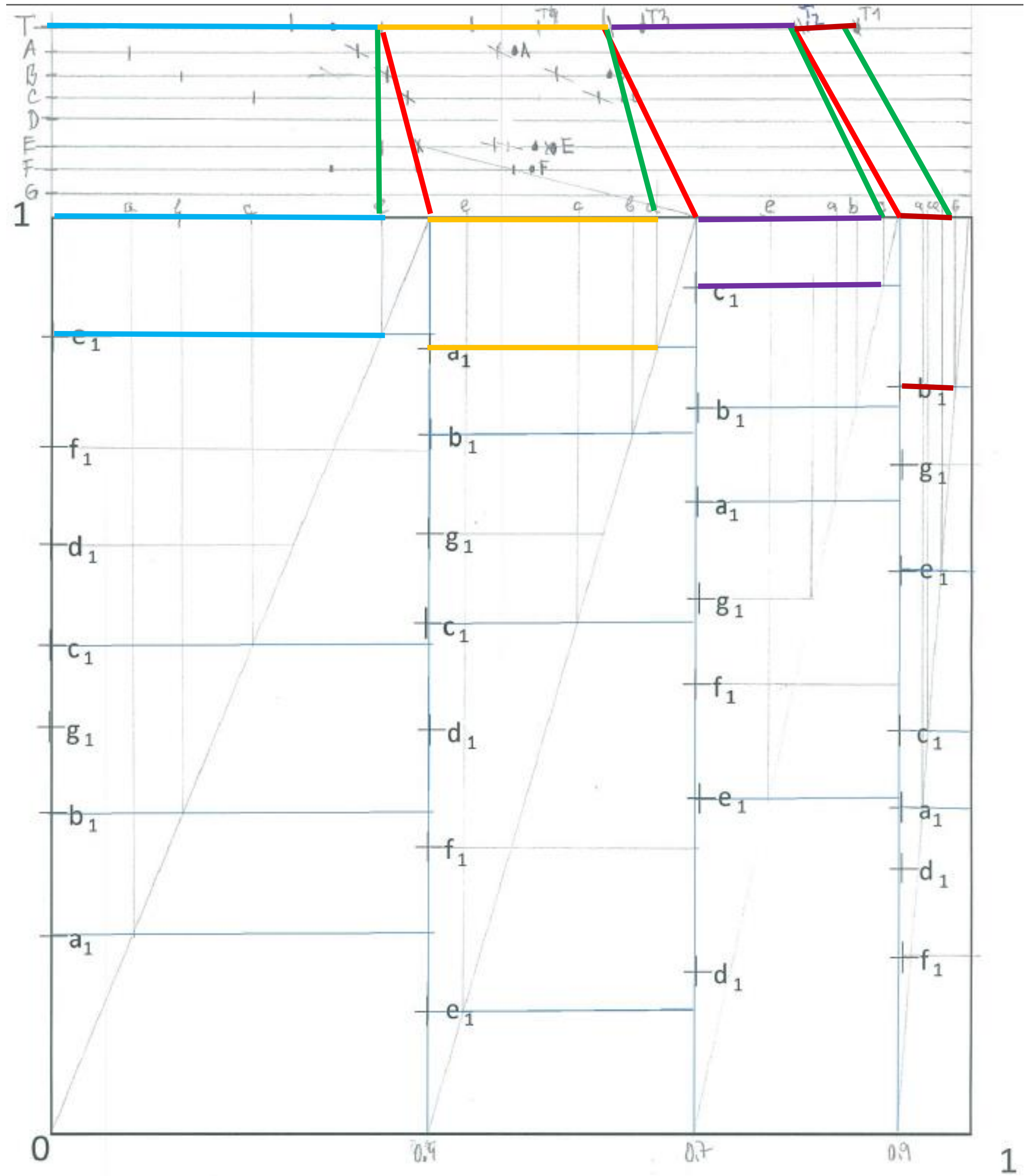
Above this there are 8 lines (for 7 points and threshold) where sum of attribute preferences are depicted.

Diagonal line helps to calculate attribute preference.

Parallelograms help to depict addition of respective quantity.

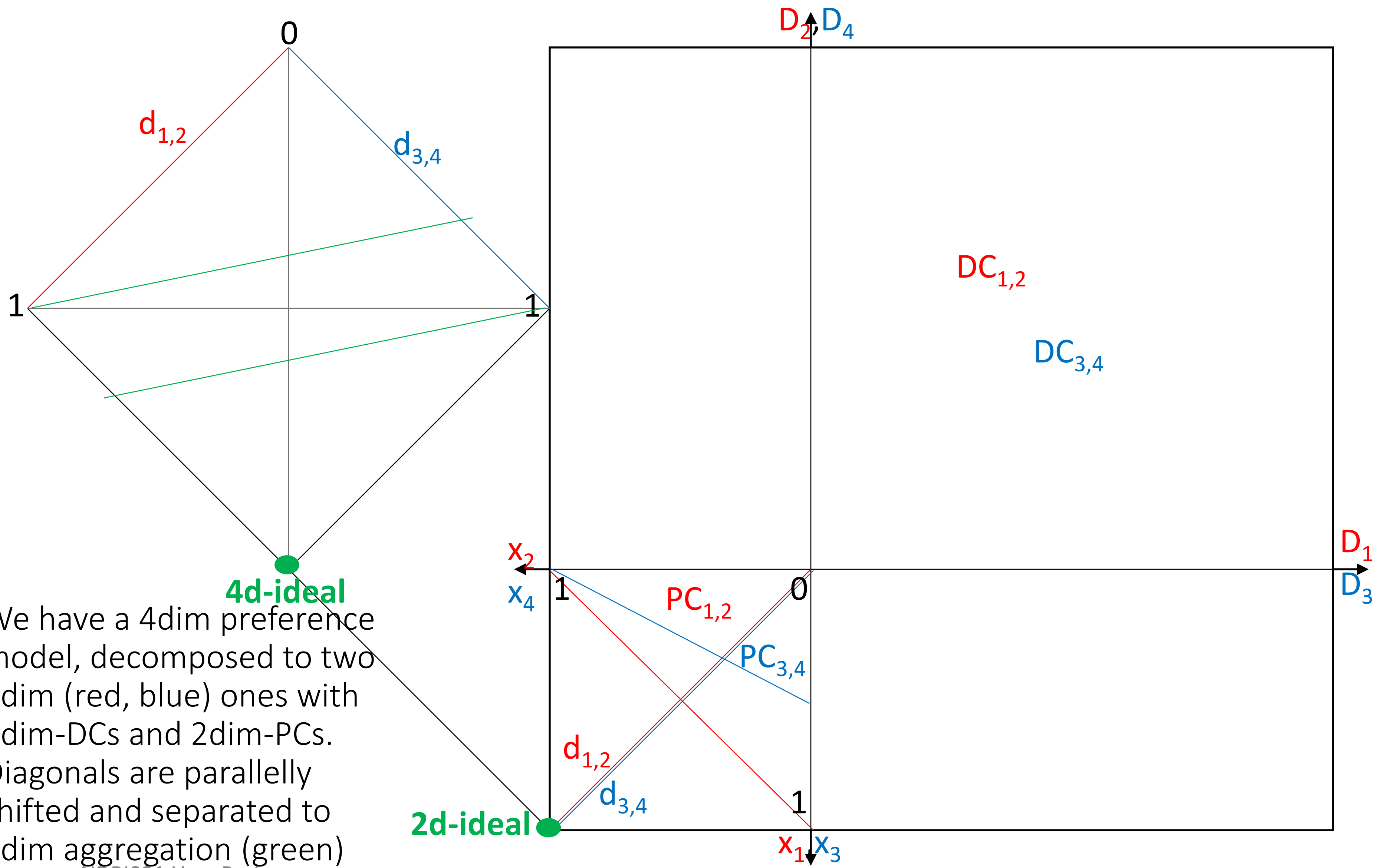
Here we depict the threshold after the first step of FLN-TA, here $T^1 = \tau^1$, …

Colors depict where the value is taken from



$$\frac{2*\frac{x_1+x_2}{2}+3*\frac{2*x_3+x_4}{3}}{5}=\frac{2*y_{1,2}+3*y_{3,4}}{5}=z$$

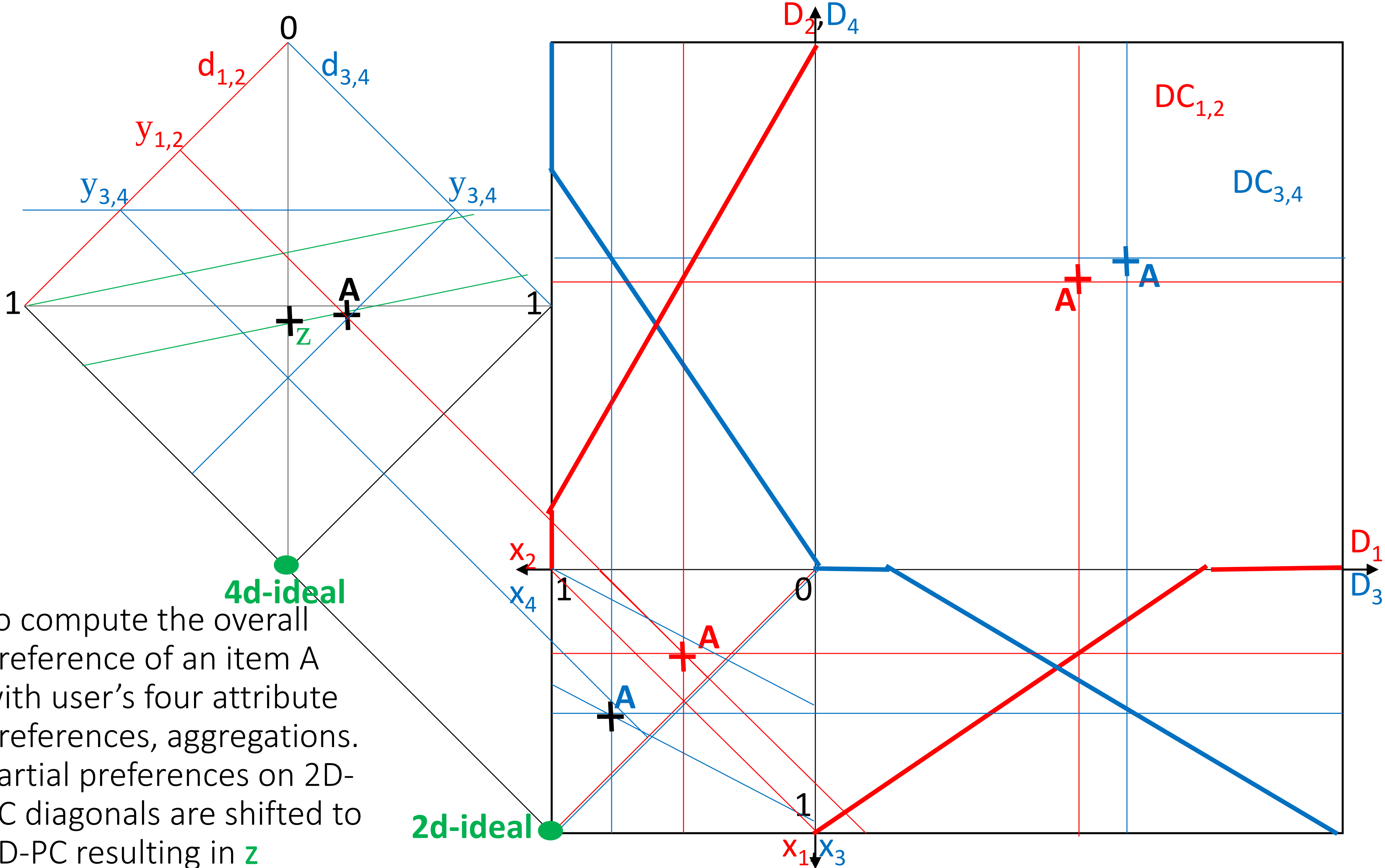
4dim framework



We have a 4dim preference model, decomposed to two 2dim (red, blue) ones with 2dim-DCs and 2dim-PCs. Diagonals are parallelly shifted and separated to 4dim aggregation (green)

Two 2D-DC → 4D-PC

$$\frac{2 * \frac{x_1 + x_2}{2} + 3 * \frac{2 * x_3 + x_4}{3}}{5} = \frac{2 * y_{1,2} + 3 * y_{3,4}}{5} = z$$



To compute the overall preference of an item A with user's four attribute preferences, aggregations. Partial preferences on 2D-PC diagonals are shifted to 4D-PC resulting in z

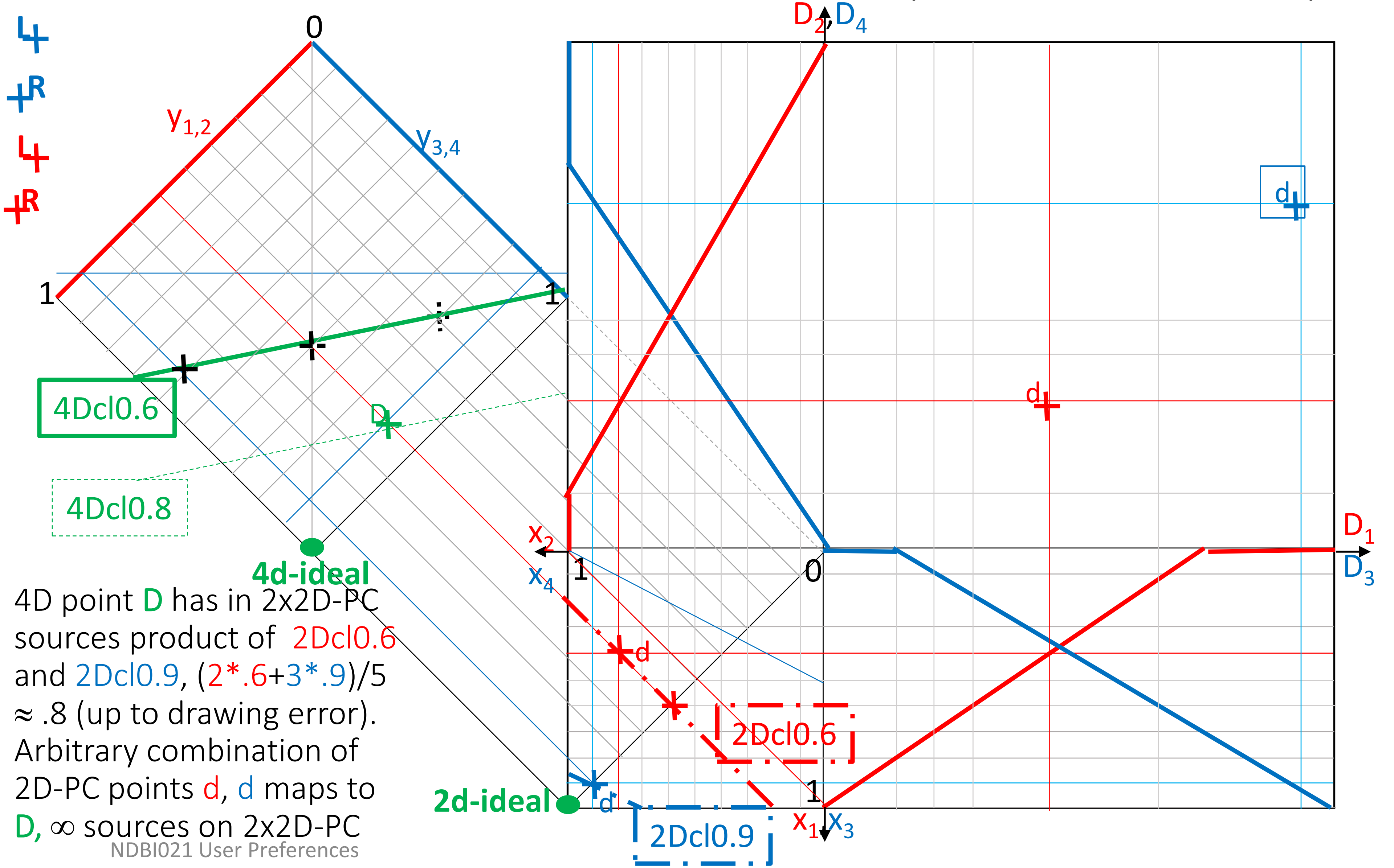
$$\frac{2 * \frac{x_1 + x_2}{2} + 3 * \frac{2 * x_3 + x_4}{3}}{5} = \frac{2 * y_{1,2} + 3 * y_{3,4}}{5} = z$$

Starting with 4dim

- 4 dim deduction – easy part
  - We know the whole model
  - DC → PC it is easy to graphical calculate an item overall preference
- 4 dim from PC → DC
  - Calculate contour lines graphically is the same as ask query:
  - “which items are preferred more than ...”
  - It is a little bit more involved as 4 dim contour lines are **3dim hyper cubes**
- Induction will be challenging
  - Because FLN-LMPM model needs to know each attribute preference separately, and
  - And our graphics (on paper) is 2 dimensional ...

$$\frac{2 * \frac{x_1 + x_2}{2} + 3 * \frac{2 * x_3 + x_4}{3}}{5} = \frac{2 * y_{1,2} + 3 * y_{3,4}}{5} = z$$

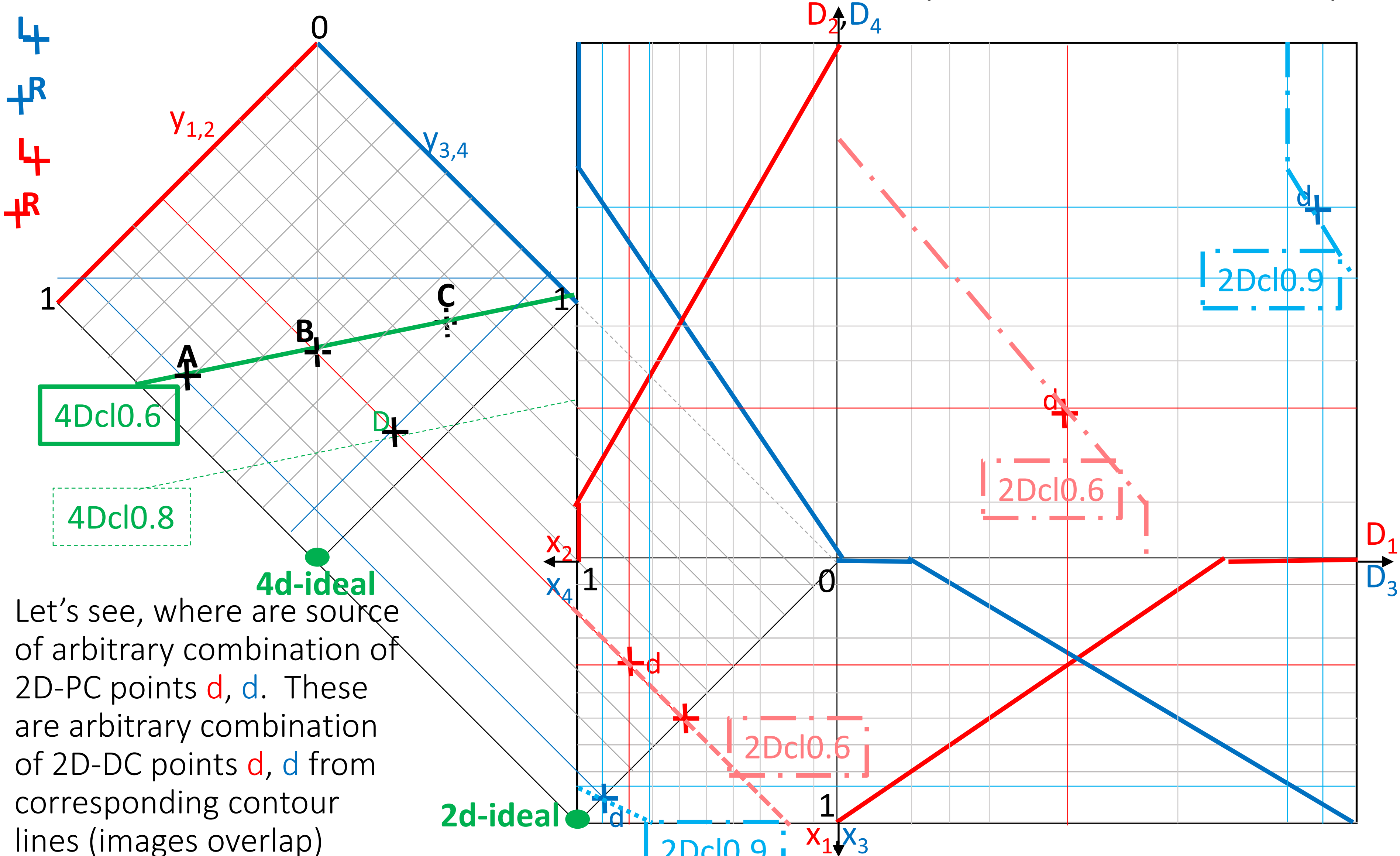
4D-PC point on 0.8-4d cl to pairs of 2d cl's, step 1



4D point D has in 2x2D-PC sources product of 2Dcl0.6 and 2Dcl0.9, (2*.6+3*.9)/5 ≈ .8 (up to drawing error). Arbitrary combination of 2D-PC points d, d maps to D, ∞ sources on 2x2D-PC

$$\frac{2 * \frac{x_1 + x_2}{2} + 3 * \frac{2 * x_3 + x_4}{3}}{5} = \frac{2 * y_{1,2} + 3 * y_{3,4}}{5} = z$$

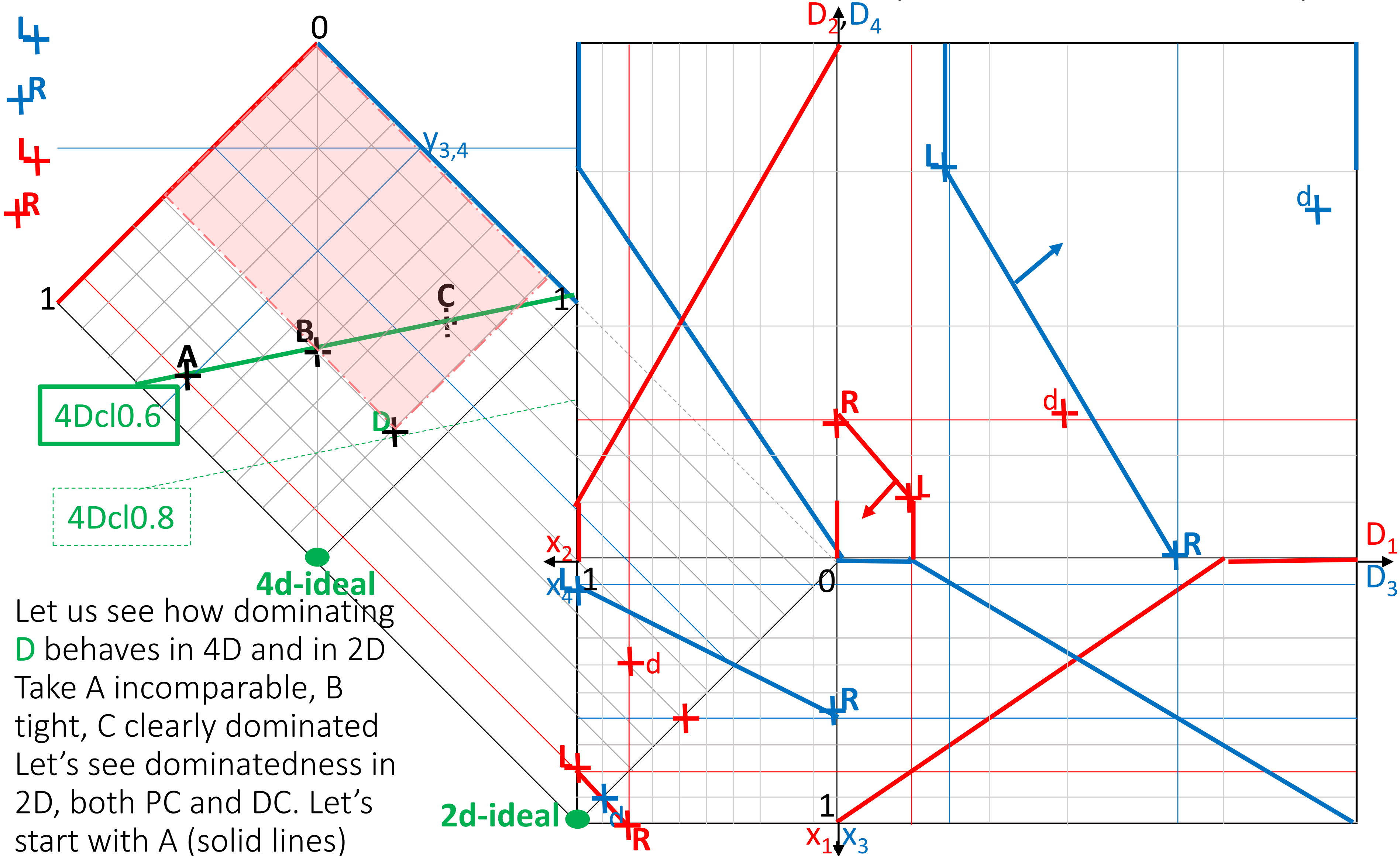
4D-PC point on 0.8-4d cl to pairs of 2d cl's, step 2



Let's see, where are source of arbitrary combination of 2D-PC points d, d. These are arbitrary combination of 2D-DC points d, d from corresponding contour lines (images overlap)

0.6-4d cl to a system of pairs of 2d cl's, step 1

$$\frac{2 * \frac{x_1 + x_2}{2} + 3 * \frac{2 * x_3 + x_4}{3}}{5} = \frac{2 * y_{1,2} + 3 * y_{3,4}}{5} = z$$



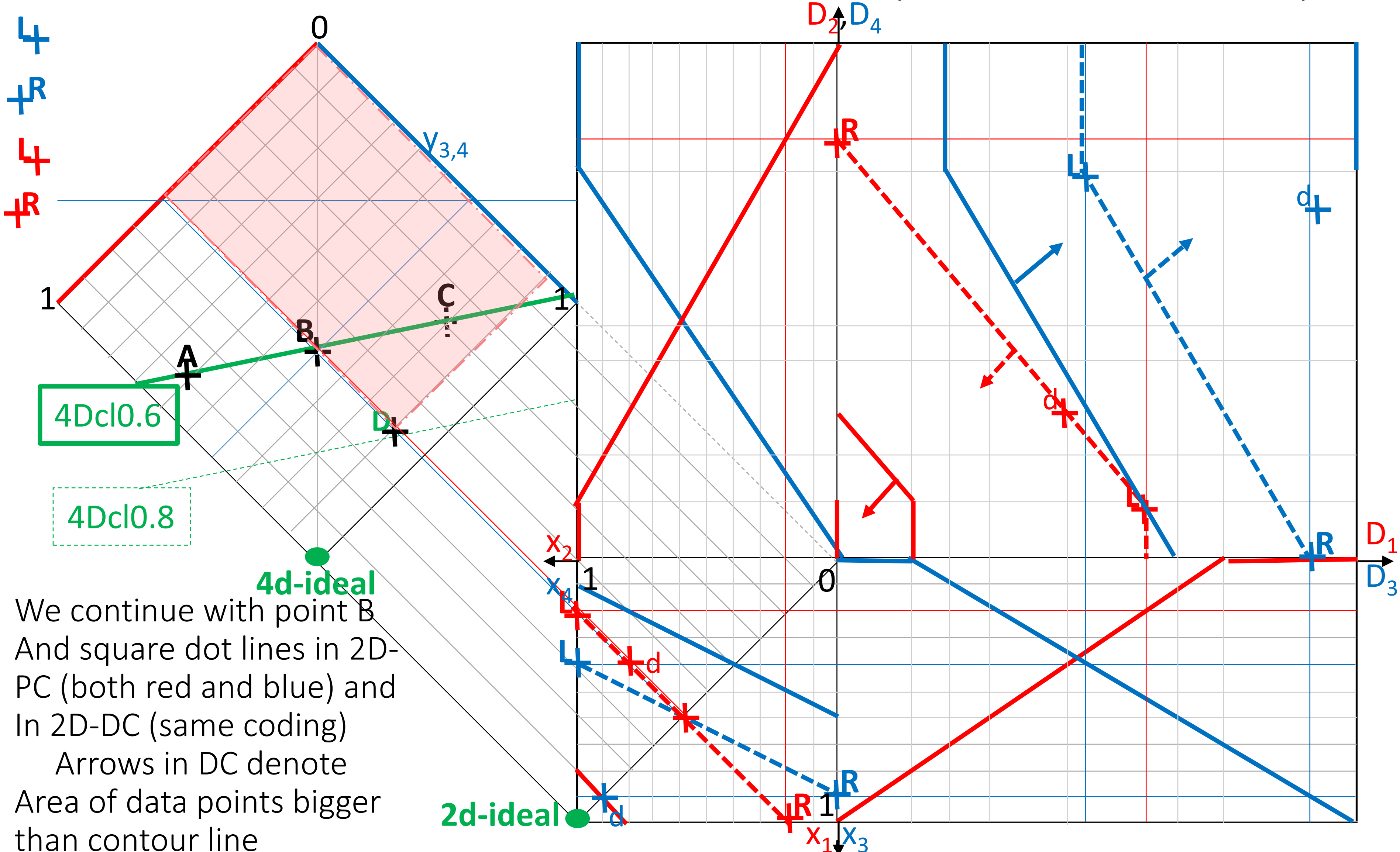
Let us see how dominating D behaves in 4D and in 2D

Take A incomparable, B tight, C clearly dominated

Let's see dominatedness in 2D, both PC and DC. Let's start with A (solid lines)

$$\frac{2 * \frac{x_1 + x_2}{2} + 3 * \frac{2 * x_3 + x_4}{3}}{5} = \frac{2 * y_{1,2} + 3 * y_{3,4}}{5} = z$$

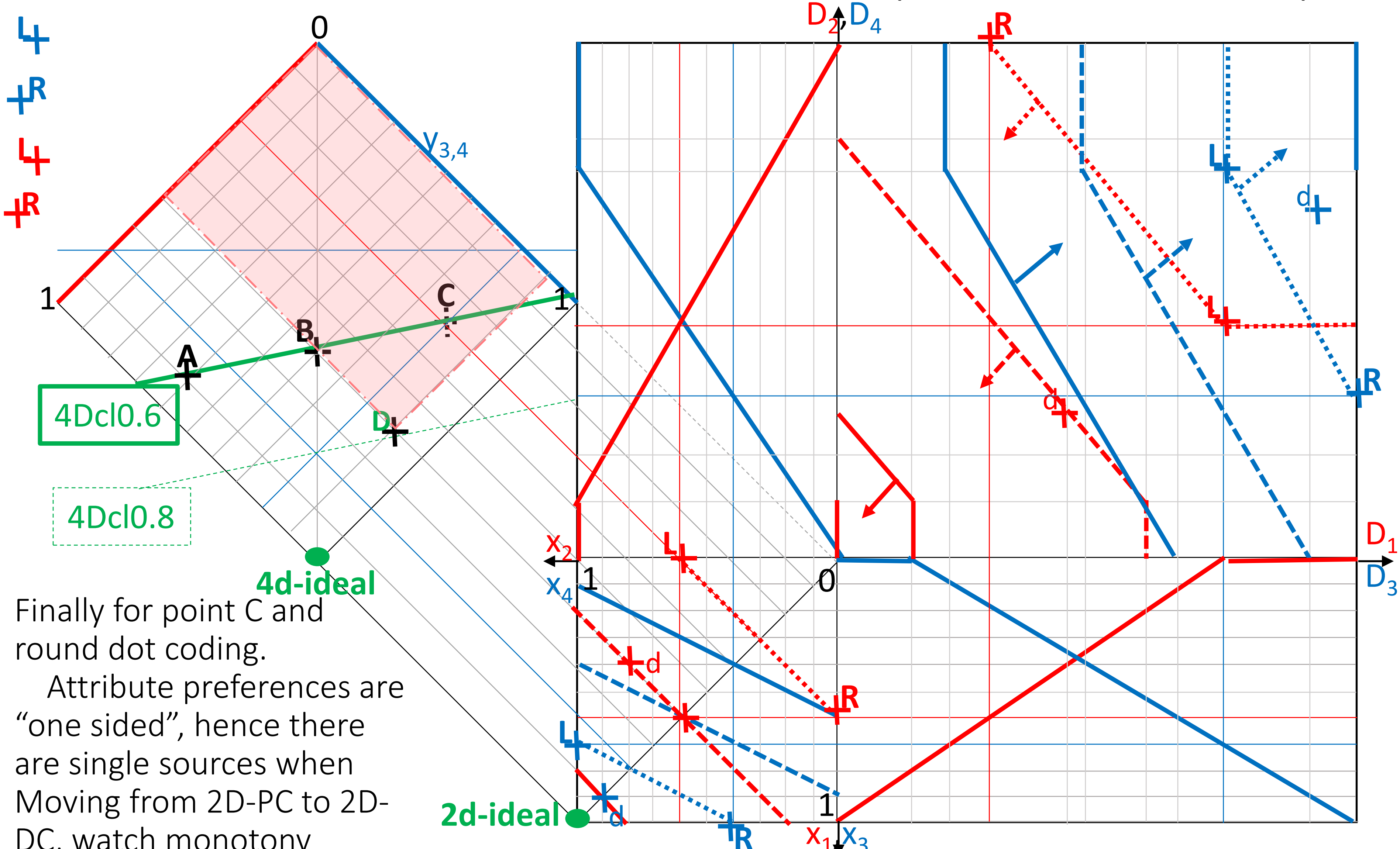
0.6-4d cl to a system of pairs of 2d cl's, step 2



We continue with point B
And square dot lines in 2D-PC (both red and blue) and
In 2D-DC (same coding)
Arrows in DC denote
Area of data points bigger than contour line

$$\frac{2*\frac{x_1+x_2}{2}+3*\frac{2*x_3+x_4}{3}}{5}=\frac{2*y_{1,2}+3*y_{3,4}}{5}=z$$

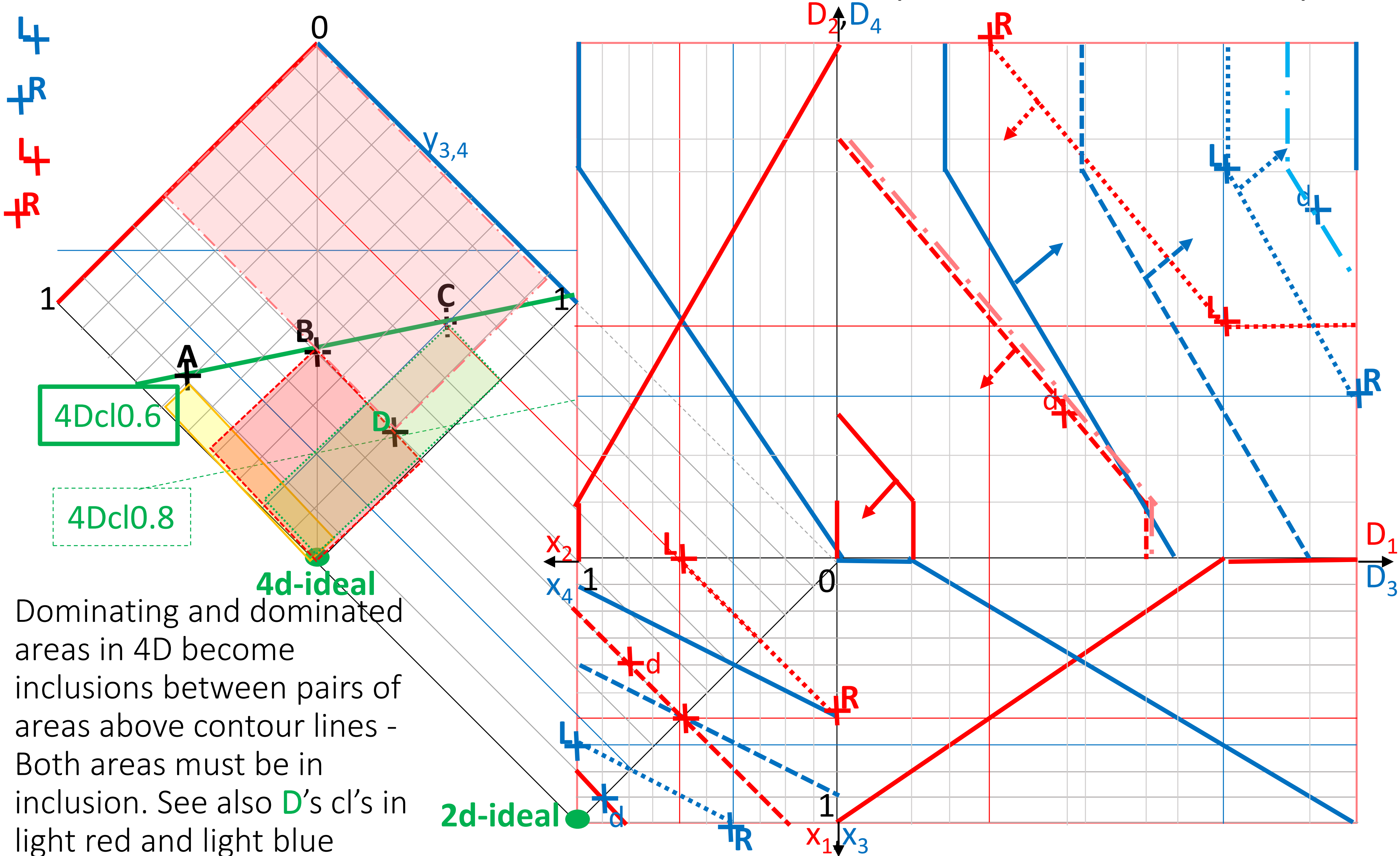
0.6-4d cl to a system of pairs of 2d cl's, step 3



Finally for point C and round dot coding.
Attribute preferences are "one sided", hence there are single sources when Moving from 2D-PC to 2D-DC, watch monotony

$$\frac{2 * \frac{x_1 + x_2}{2} + 3 * \frac{2 * x_3 + x_4}{3}}{5} = \frac{2 * y_{1,2} + 3 * y_{3,4}}{5} = z$$

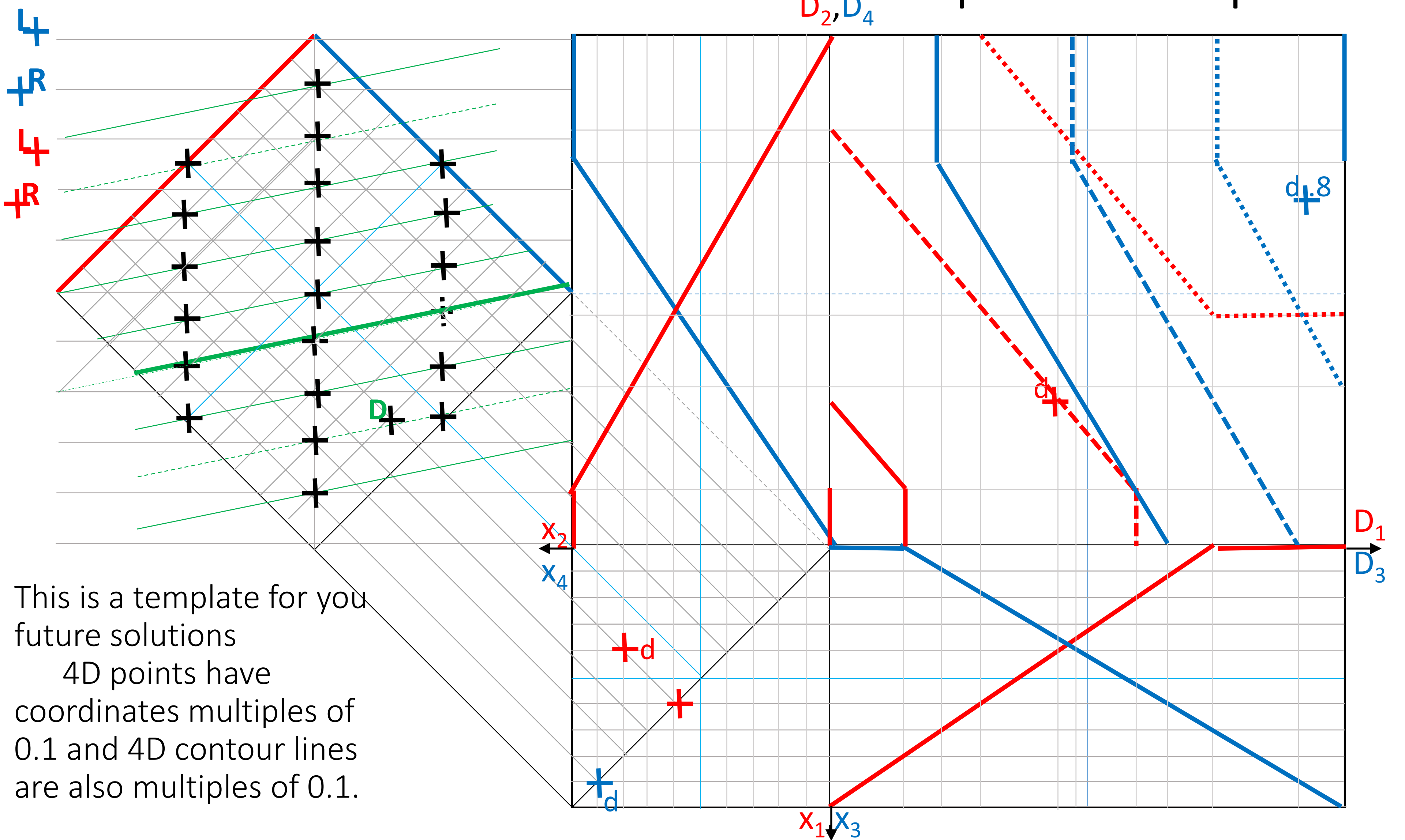
0.6-4d cl to a system of pairs of 2d cl’s, step 4



Dominating and dominated areas in 4D become inclusions between pairs of areas above contour lines - Both areas must be in inclusion. See also D’s cl’s in light red and light blue

4d points easy to depict&compute

$$\frac{2 * \frac{x_1 + x_2}{2} + 3 * \frac{2 * x_3 + x_4}{3}}{5} = \frac{2 * y_{1,2} + 3 * y_{3,4}}{5} = z$$

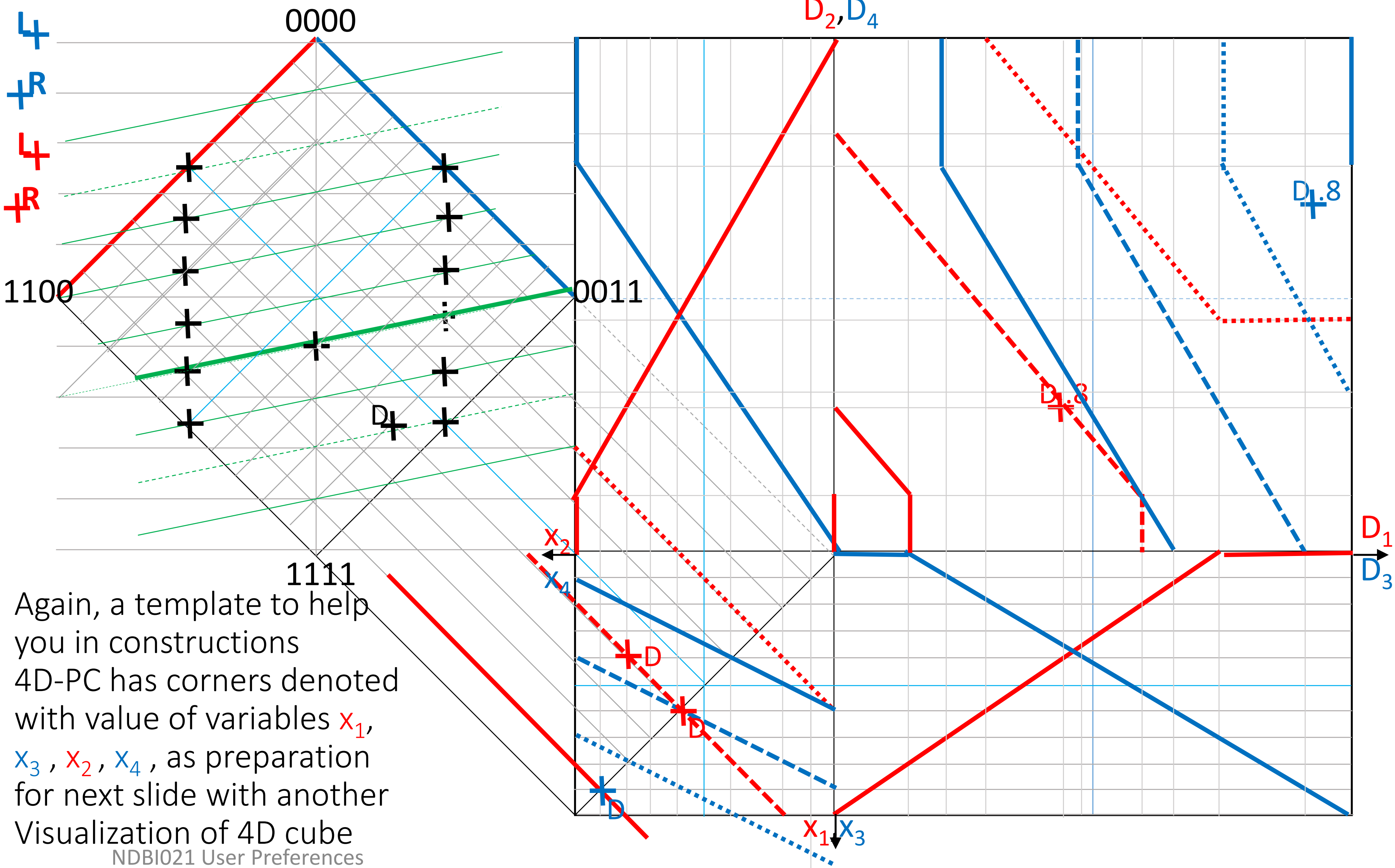


This is a template for you future solutions

4D points have coordinates multiples of 0.1 and 4D contour lines are also multiples of 0.1.

To compare with 4d cube

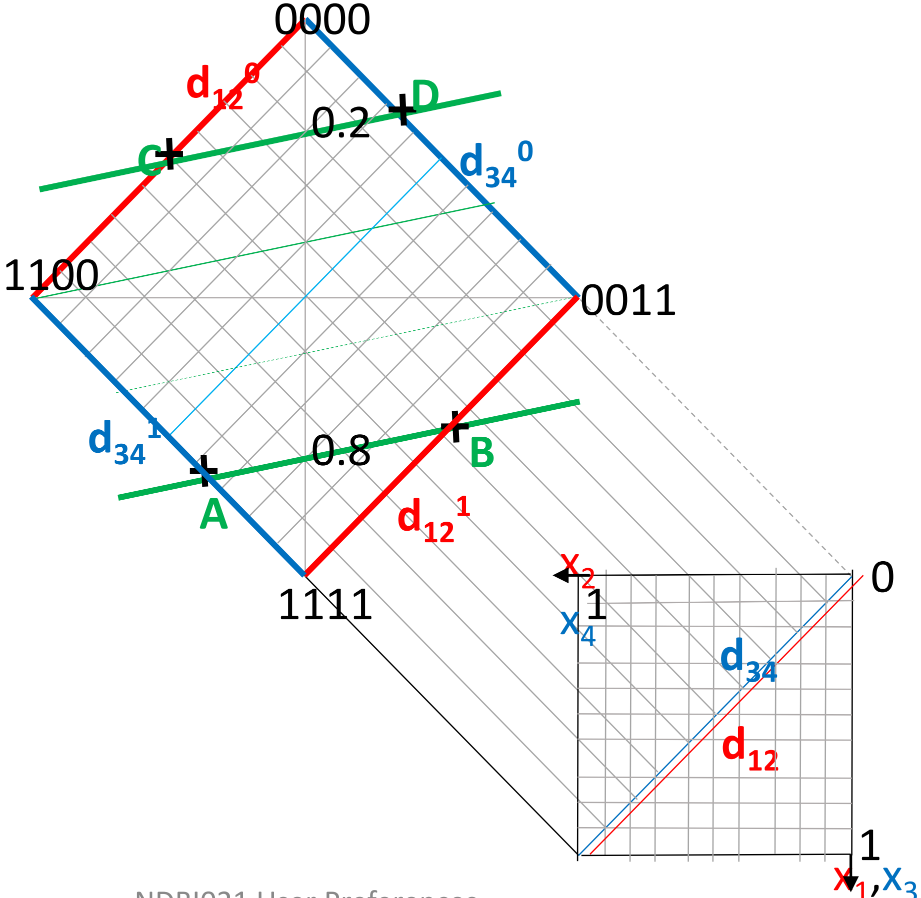
$$\frac{2*\frac{x_1+x_2}{2}+3*\frac{2*x_3+x_4}{3}}{5}=\frac{2*y_{1,2}+3*y_{3,4}}{5}=z$$

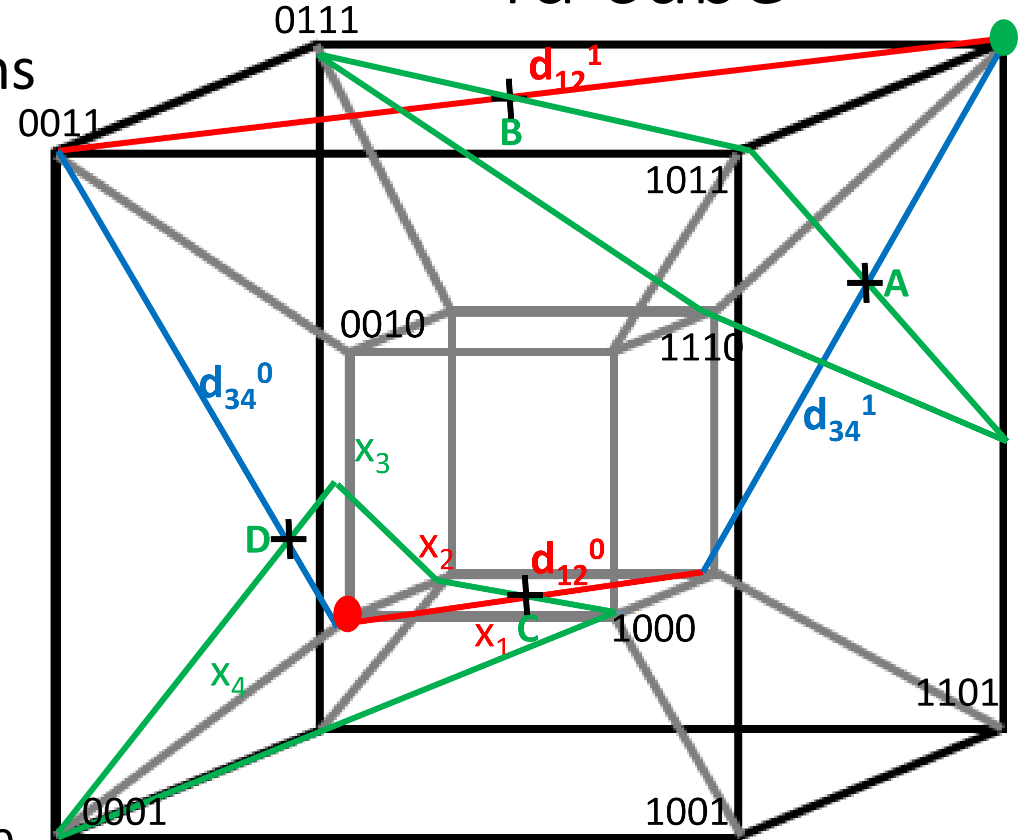


Again, a template to help you in constructions 4D-PC has corners denoted with value of variables x_1, x_3 , x_2 , x_4 , as preparation for next slide with another Visualization of 4D cube

To compare with 4d cube

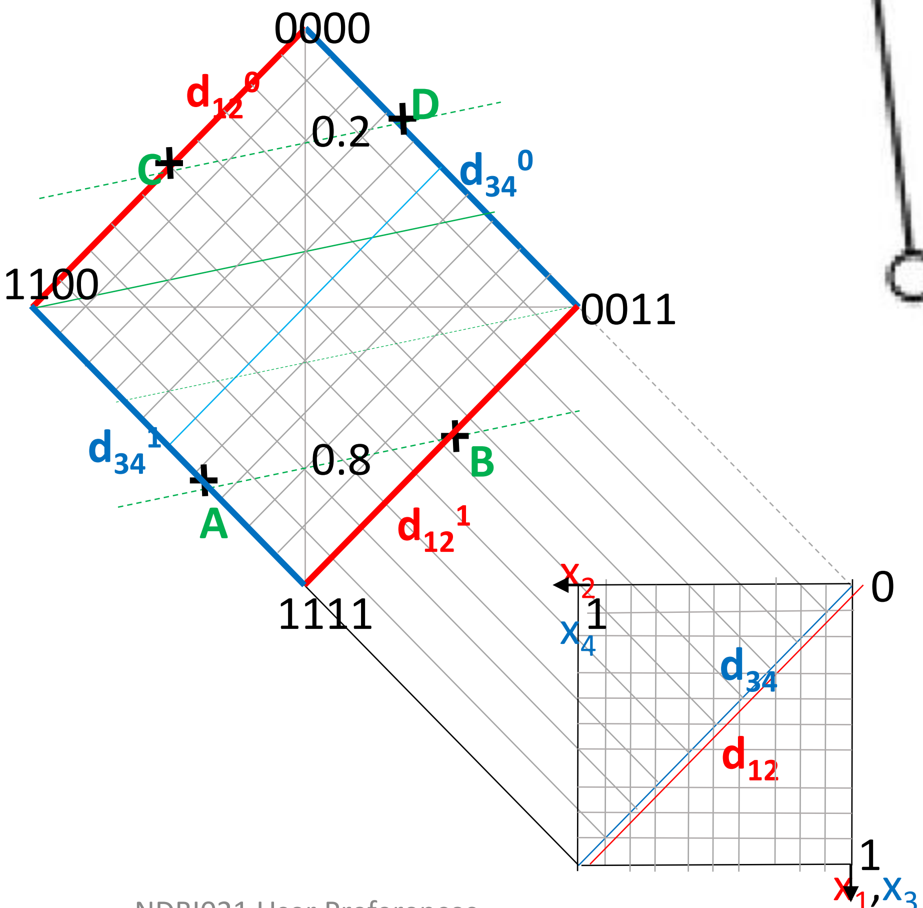
0.2/0.8 contour line in 4D is a 3D hypercube, here only intersections with 4D-cube faces are depicted

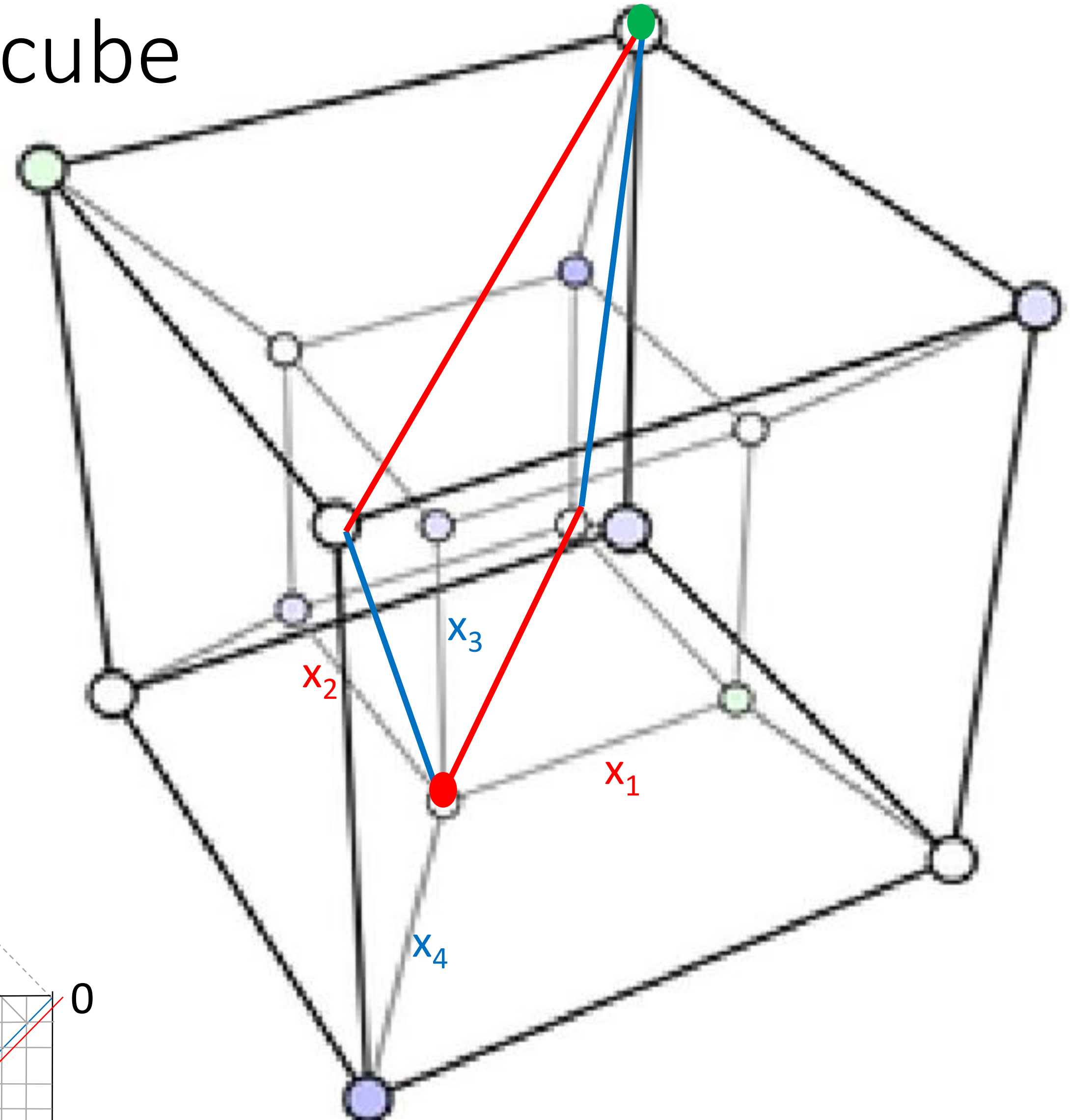




Each visualization has some advantages and disadvantages, please comment

Another view of 4d cube construct all as in previous slide

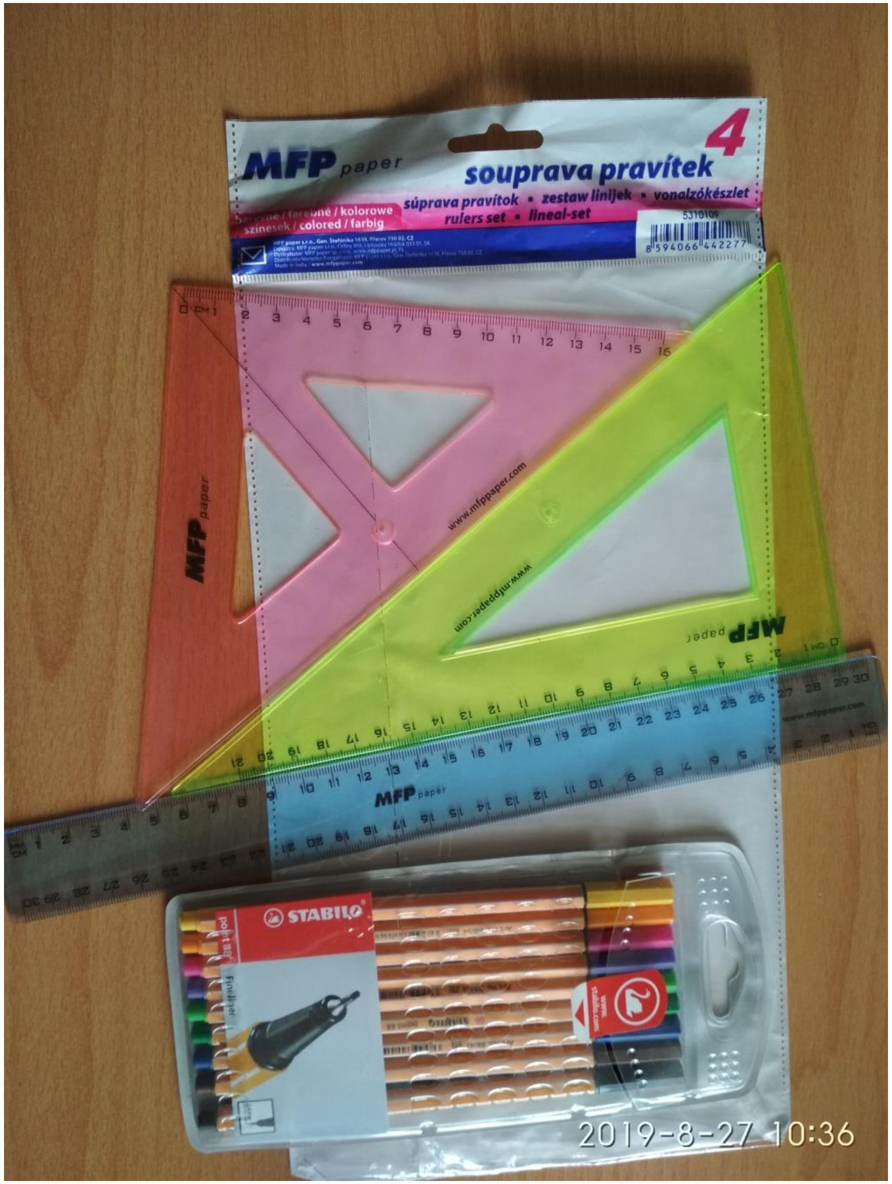




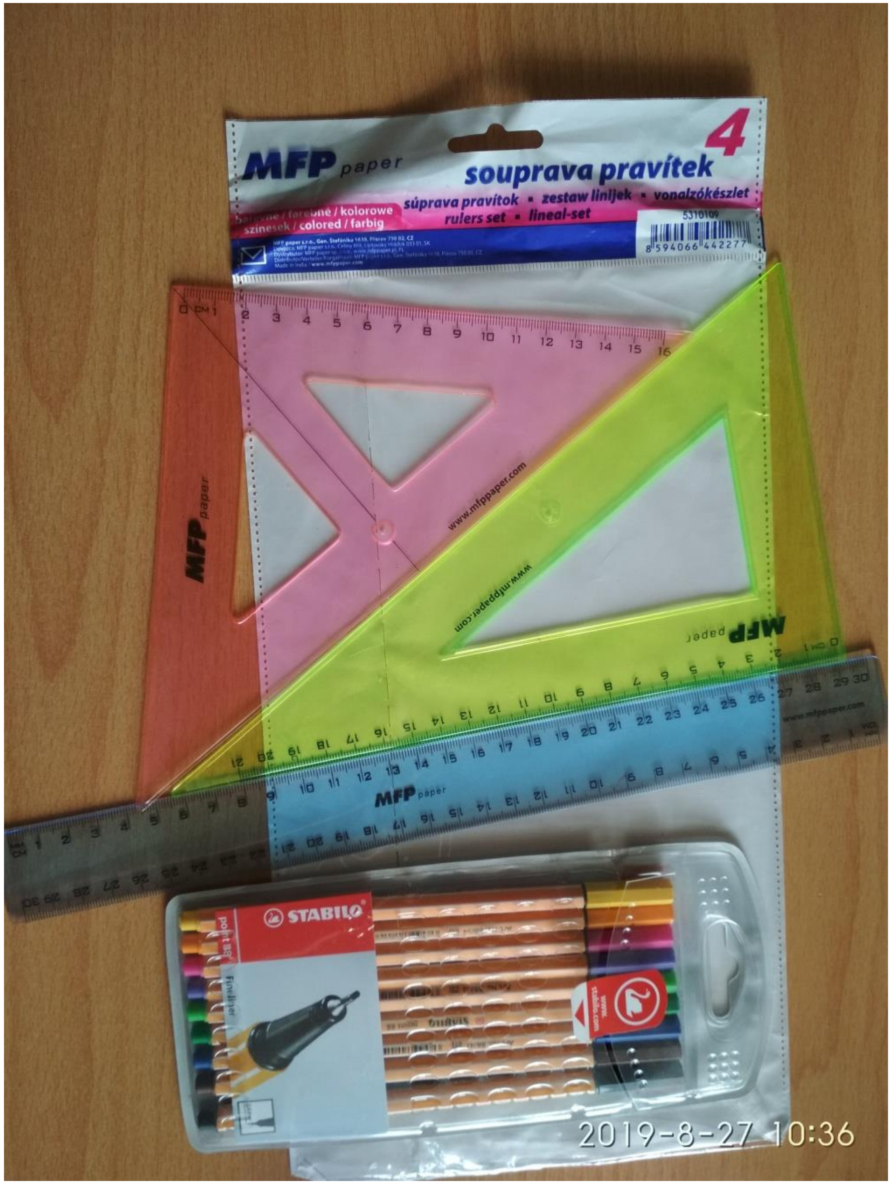
What is preserved? What not? Parallelism, ratio of distances? ...

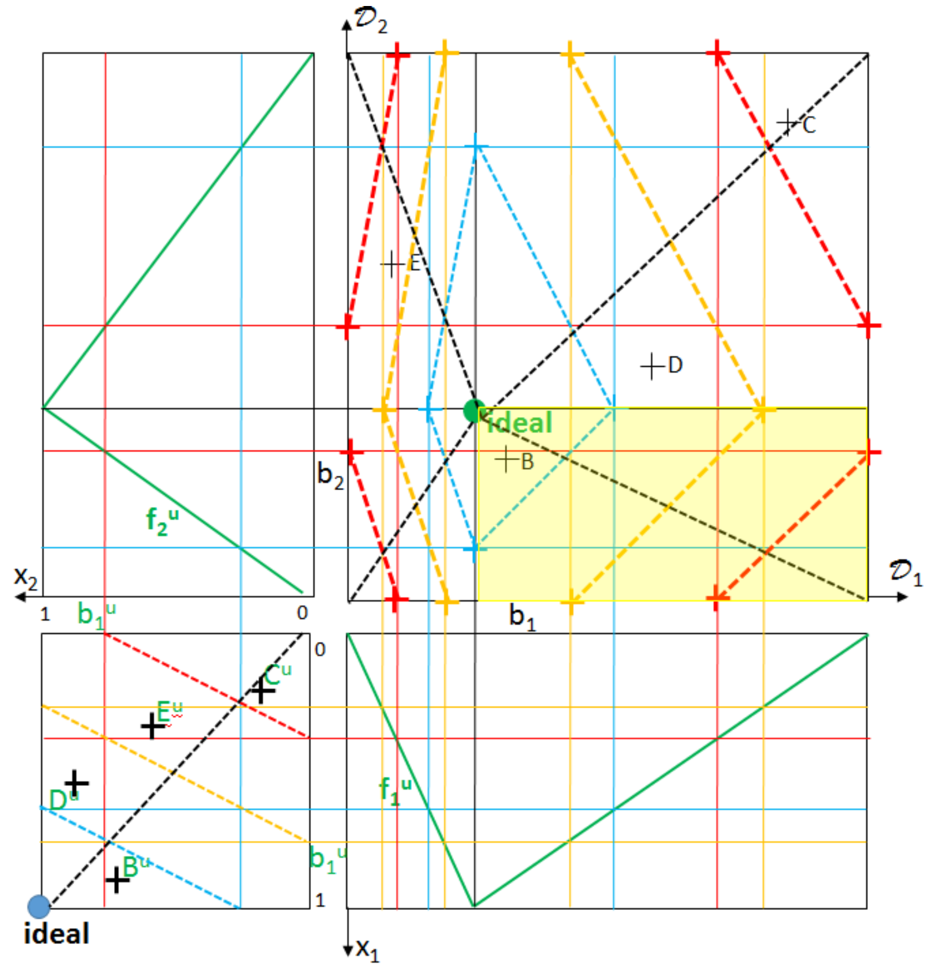
No coding, simulation using drawing tools

Main Railway station, southern wing



Our solutions will look like …

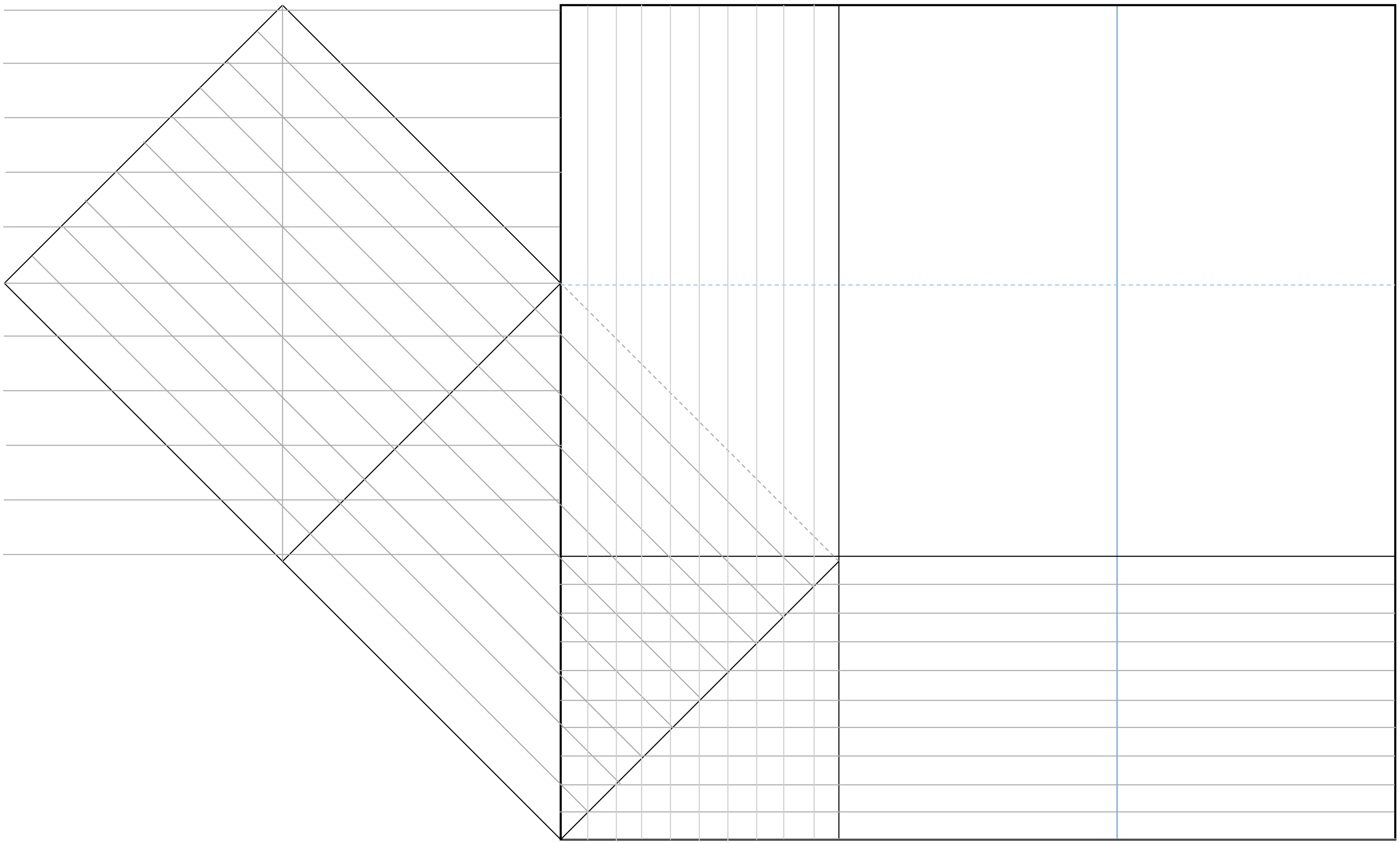




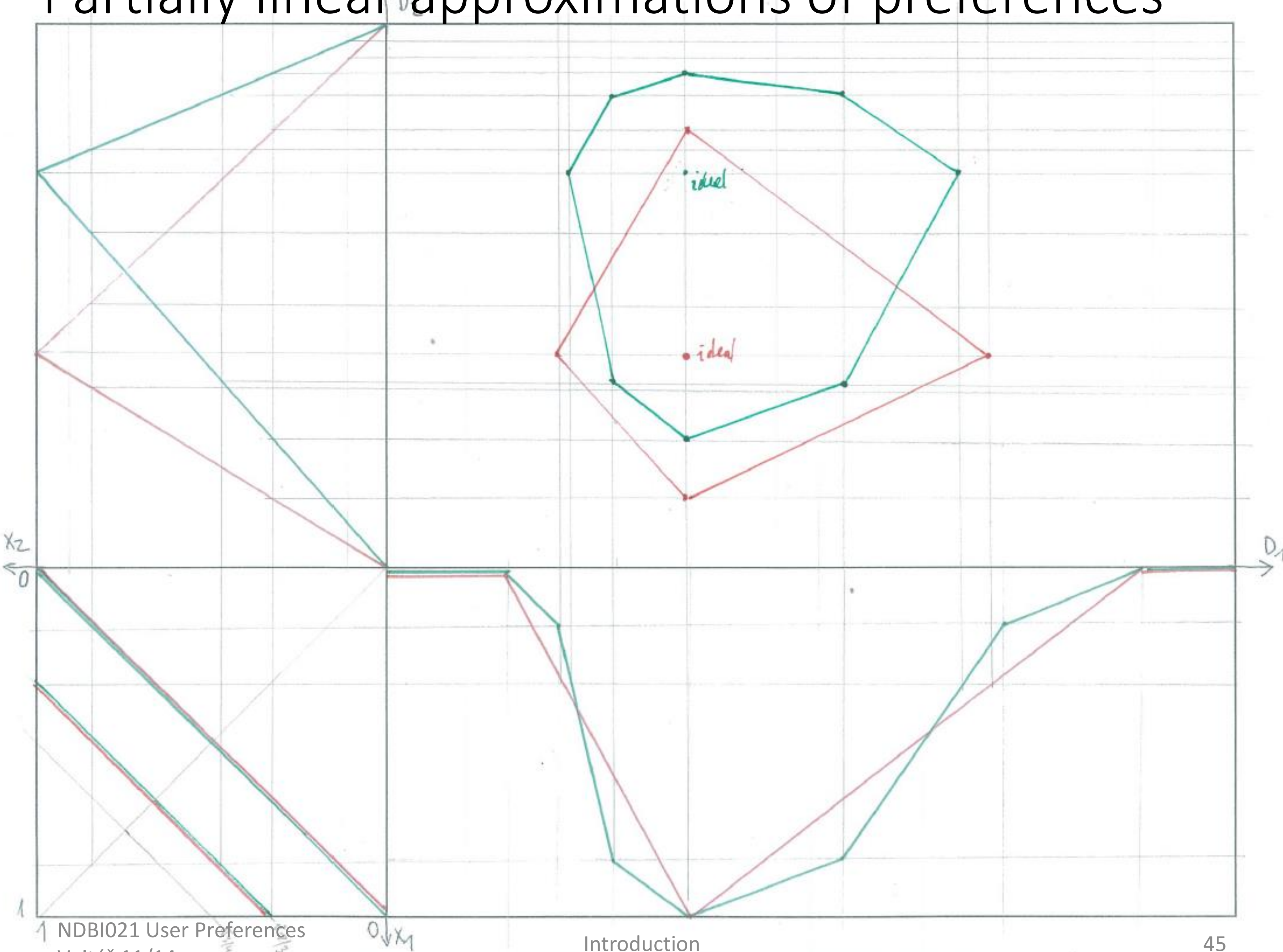
Questions?

Comments?

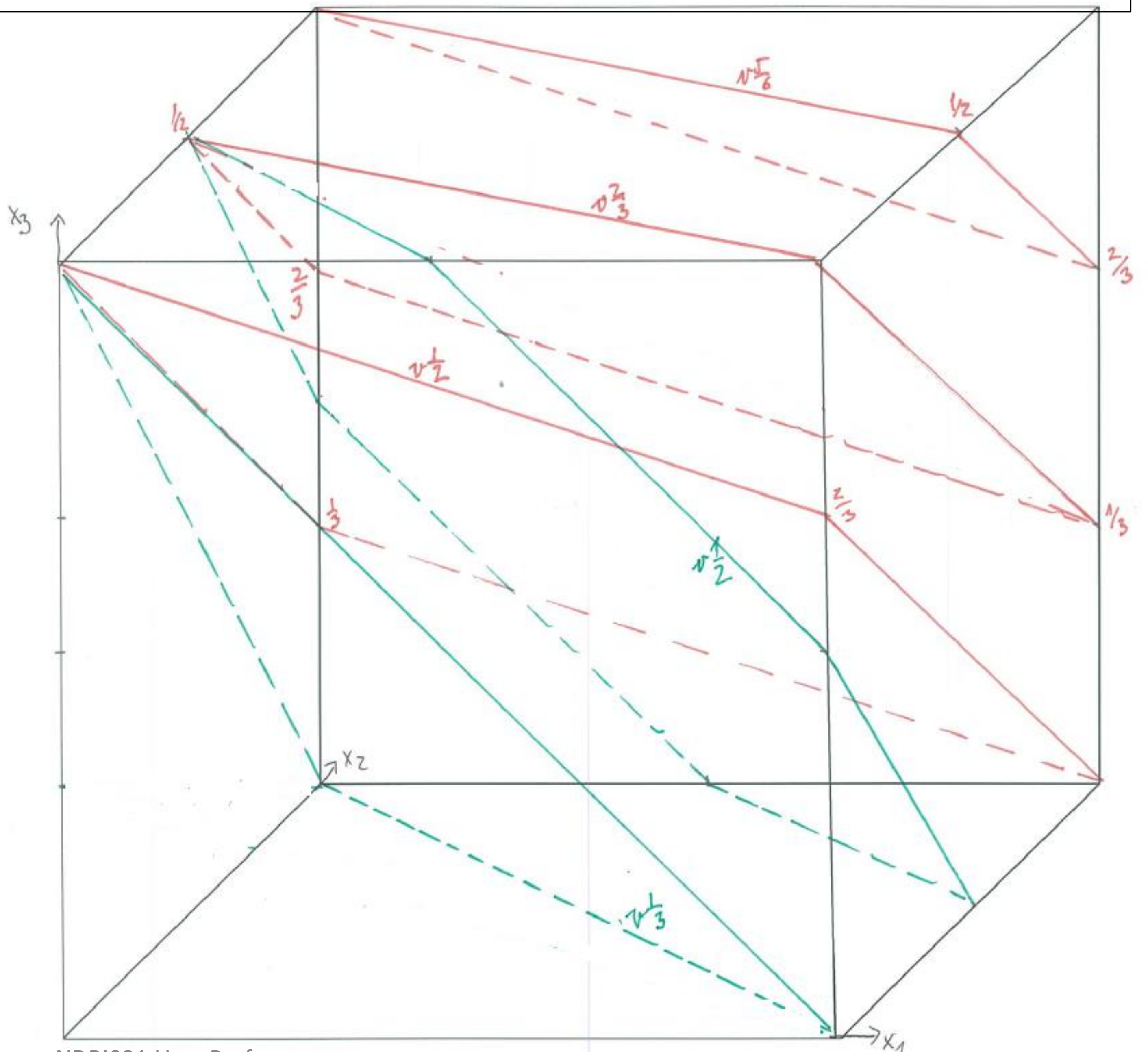
We will use framework for 4dim, ...



Partially linear approximations of preferences



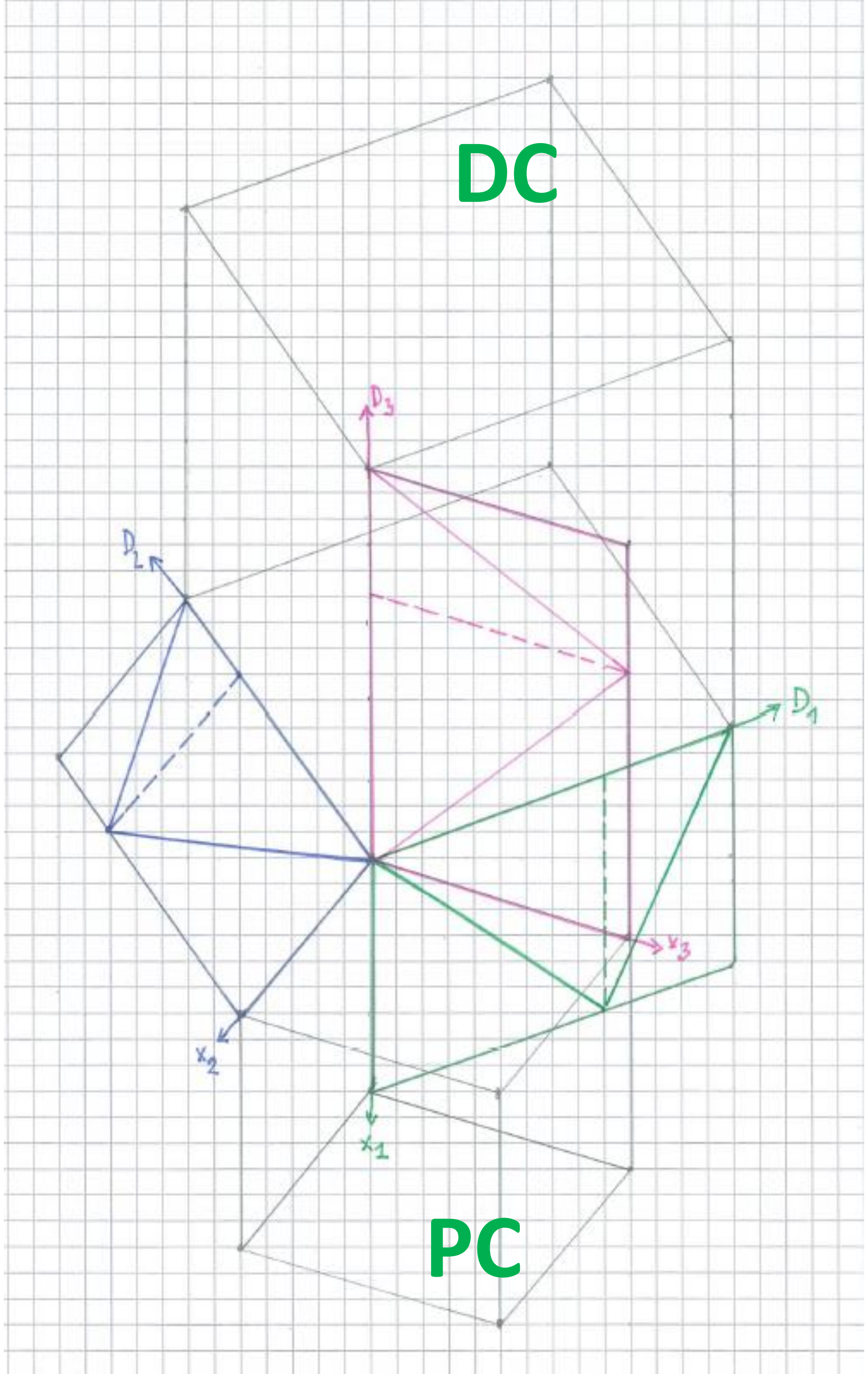
Preference cube in 3D with contour surface wrt different aggregaations



$$\frac{x_1 + 2x_2 + 3x_3}{6}$$

$$\frac{x_1 + x_2 + x_3}{3}$$

3D-DC-PC



Dynamical model – three sessions – moving ideal points (aggregations remain same)

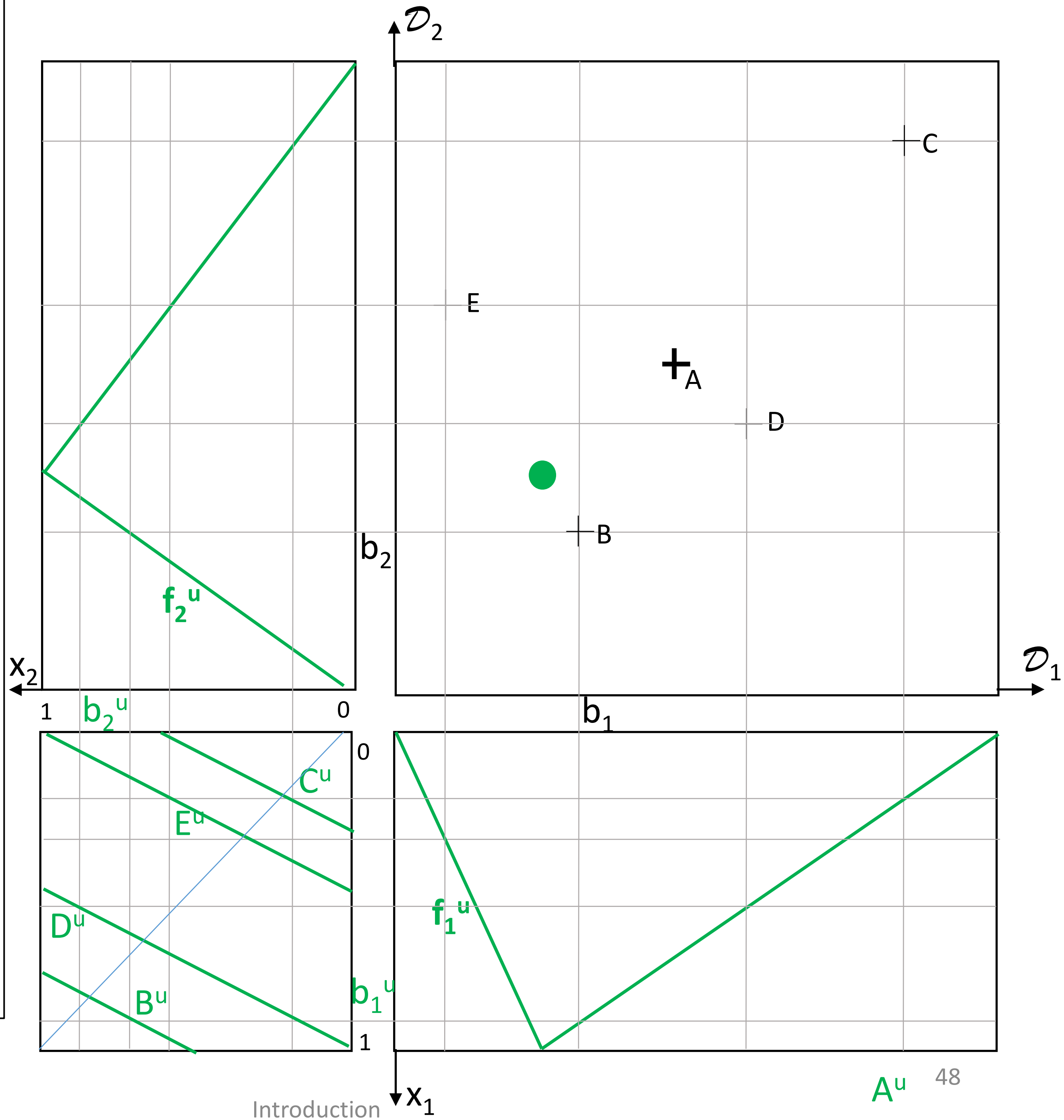
Simulation of development in time

Starting vector of attribute preferences $\mathbf{f^0}$ and aggregation $\mathbf{t^0}$ define an user $\mathbf{u^0_{f,t}} = \mathbf{u^0}$ in time 0. Depict contour line in DC-data cube.

Assume user clicks on third item. In time 1, $\mathbf{t^0} = \mathbf{t^1}$, ideal is clicked item (triangular max-min shape remains).

In time 1 user clicks on second item – this becomes ideal in time 2.

Describe order in time 2.



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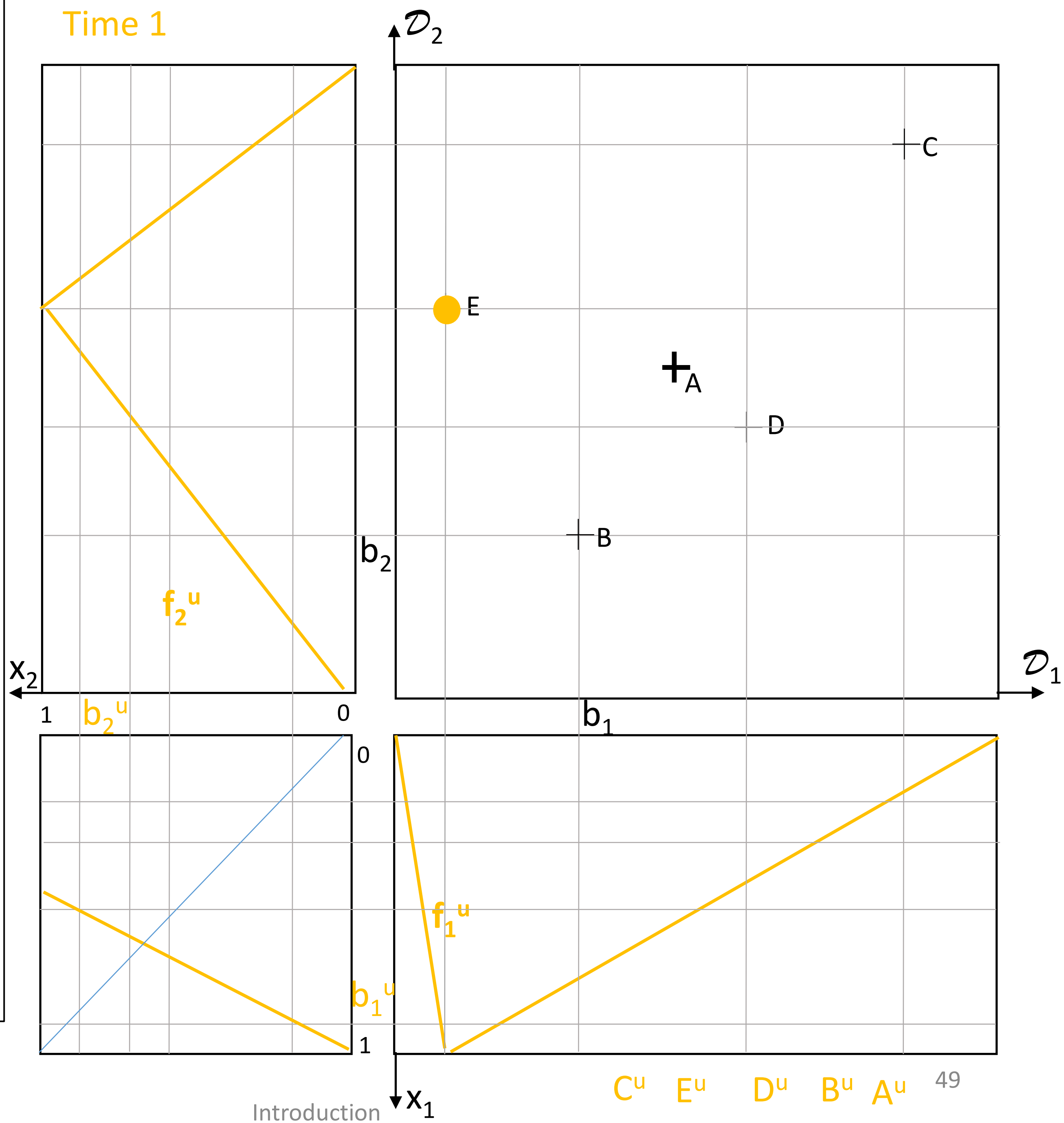

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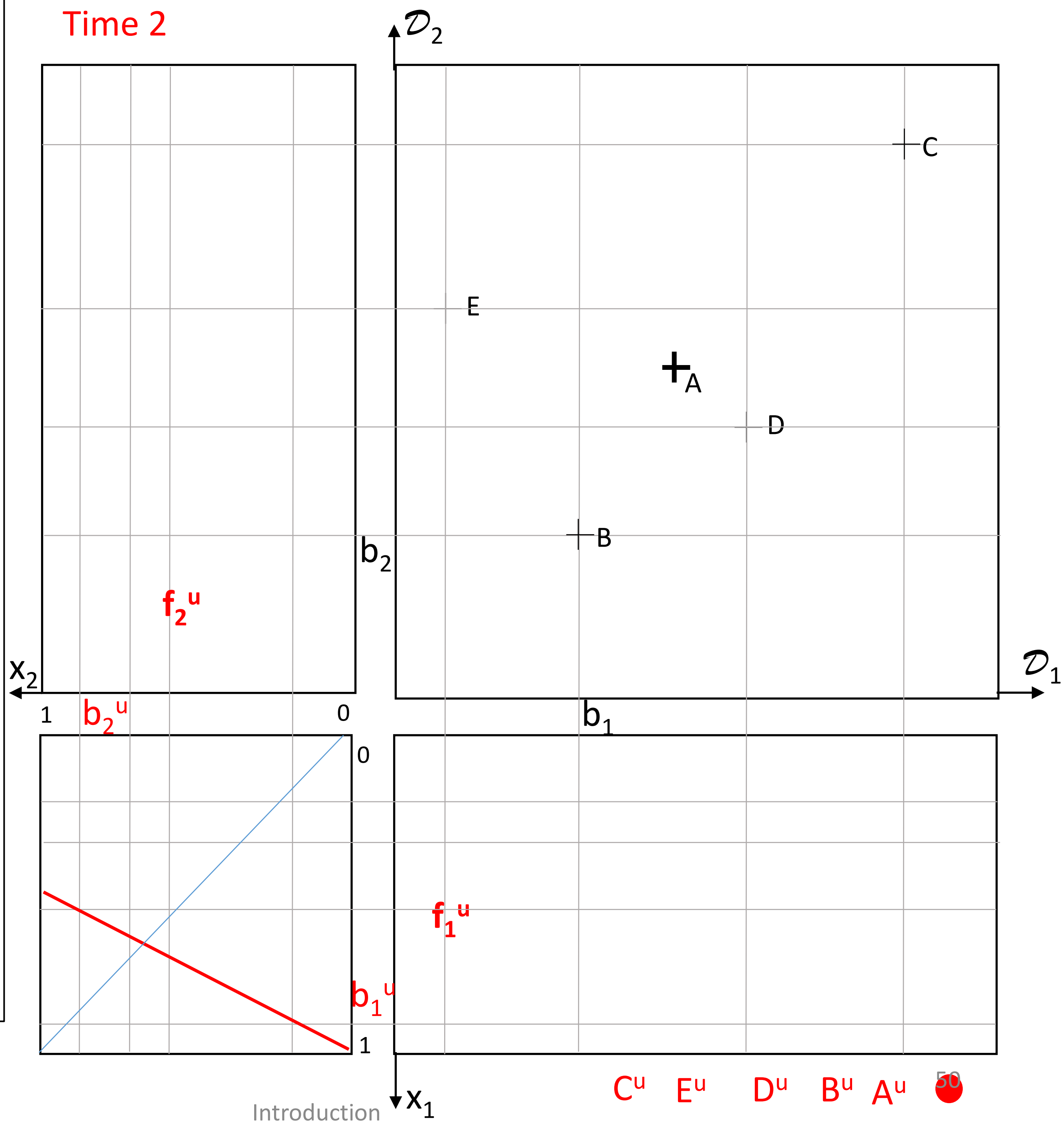

Dynamical model – three sessions – moving ideal points and **moving aggregation**

Simulation of development in time

Starting vector of attribute preferences $\mathbf{f^0}$ and aggregation $\mathbf{t^0}$ define an user $\mathbf{u^0_{f,t}} = \mathbf{u^0}$ in time 0. Depict contour line in DC-data cube.

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