

# Linguistic Approximation: Outline

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- The Engineering Solution: the PR Approach
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- Example of Applications

# Linguistic Approximation: Definition

- What is it?
  - The process of *labeling* a membership distribution with a symbol whose meaning is *the closest* (according to some distance) to the meaning of the unlabelled distribution
  - In other words, we associate a label with a distribution on the basis of semantic similarity
  - Formally it is a mapping from the crisp set of all fuzzy subsets of the universe of discourse  $U$  into the language  $\ell=L(G_1)$ :  
$$LA : U \rightarrow L(G_1)$$

# Linguistic Approximation: Purpose

- Why do we need it?
  - To force the closure within a language of results of operations that do not preserve such closure
  - To simplify existing labels
  - To provide a linguistic summary of the result of an external process (approximate reasoning, extension principle, etc.)

# Problem Formulation

- The Linguistic Approximation of an unlabelled fuzzy set  $A'(u)$  is:

$$\mathbf{LA}[A'(u)] = \mathbf{S}_A$$

such that

$$d(A'(u), A(u)) = \min_{\forall A_i \in L(G_1)} d(A'(u), A_i(u))$$

# Problem Formulation

where:

- $A$  and  $A'$  are subset of the same universe  $U$
- $A'$  is the unlabelled fuzzy set
- $S_A$  is the label (sentence) corresponding to  $A(u)$
- $L(G_1)$  is the finite termset (target language)
- $d(.,.)$  is a distance satisfying the axioms of a

metric, i.e.:

$$d(A, B) > 0 \leftrightarrow (A \neq B)$$

$$d(A, B) = 0 \leftrightarrow (A = B)$$

$$d(A, B) = d(B, A)$$

$$d(A, C) \leq d(A, B) + d(B, C)$$

# Problem with This Formulation

- Dependence on Distance Selection

- Hamming Distance (First Norm)  $\| \cdot \|_1$

$$d_1(A(u_k), B(u_k)) = \frac{1}{D} \sum_{k=1}^D |A(u_k) - B(u_k)|$$

- Euclidean Distance (Second Norm)  $\| \cdot \|_2$

$$d_2(A(u_k), B(u_k)) = \left[ \frac{1}{D} \sum_{k=1}^D (A(u_k) - B(u_k))^2 \right]^{0.5}$$

- Max-based Distance (Infinite Norm)  $\| \cdot \|_\infty$

$$d_\infty(A(u_k), B(u_k)) = \max_{k=1}^D (A(u_k) - B(u_k))$$

# Problem with This Formulation

- Max-based distance

- Is too sensitive to a mismatch in one point
- Saturates ( $d=1$ ) very quickly - see Excel File

$$d_{\text{inf}}(\text{Low}, \text{More\_or\_less Low}) = 0.246$$

$$d_{\text{inf}}(\text{Low}, \text{Sort\_of Low}) = d_{\text{inf}}(\text{Low}, \text{Middle}) = d_{\text{inf}}(\text{Low}, \text{High}) = 1$$

- Hamming and Euclidean Distances

- When the distributions are disjoint, the distances reflect the sum the areas under the two distributions
- As a result we may have inconsistent distances:

$$d_1(\text{Low}, \text{High}) > d_1(\text{Very\_Low}, \text{Very\_High})$$

- It does not take uniform values within  $[0, 1]$  - only on a limited range of values

# Example

Universe	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
Low	1	0.98	0.92	0.82	0.68	0.5	0.32	0.18	0.08	0.02	0	0	0	0	0	0	0	0	0	0	0
Middle	0	0	0	0	0	0.06	0.22	0.5	0.78	0.94	1	0.94	0.78	0.5	0.22	0.06	0	0	0	0	0
High	0	0	0	0	0	0	0	0	0	0	0	0.02	0.18	0.32	0.5	0.68	0.68	0.82	0.92	0.98	1
All	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
None	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

## Connectors and Modifiers

$$\text{Very (X)} = X^2$$

$$\text{More\_or\_less (X)} = X^{0.5}$$

$$\text{Sort\_of (X)} = \text{Norm}[\text{Not Very Very (X) And More\_or\_Less (X)}]$$

$$\text{X And Y} = \text{Min (X, Y)}$$

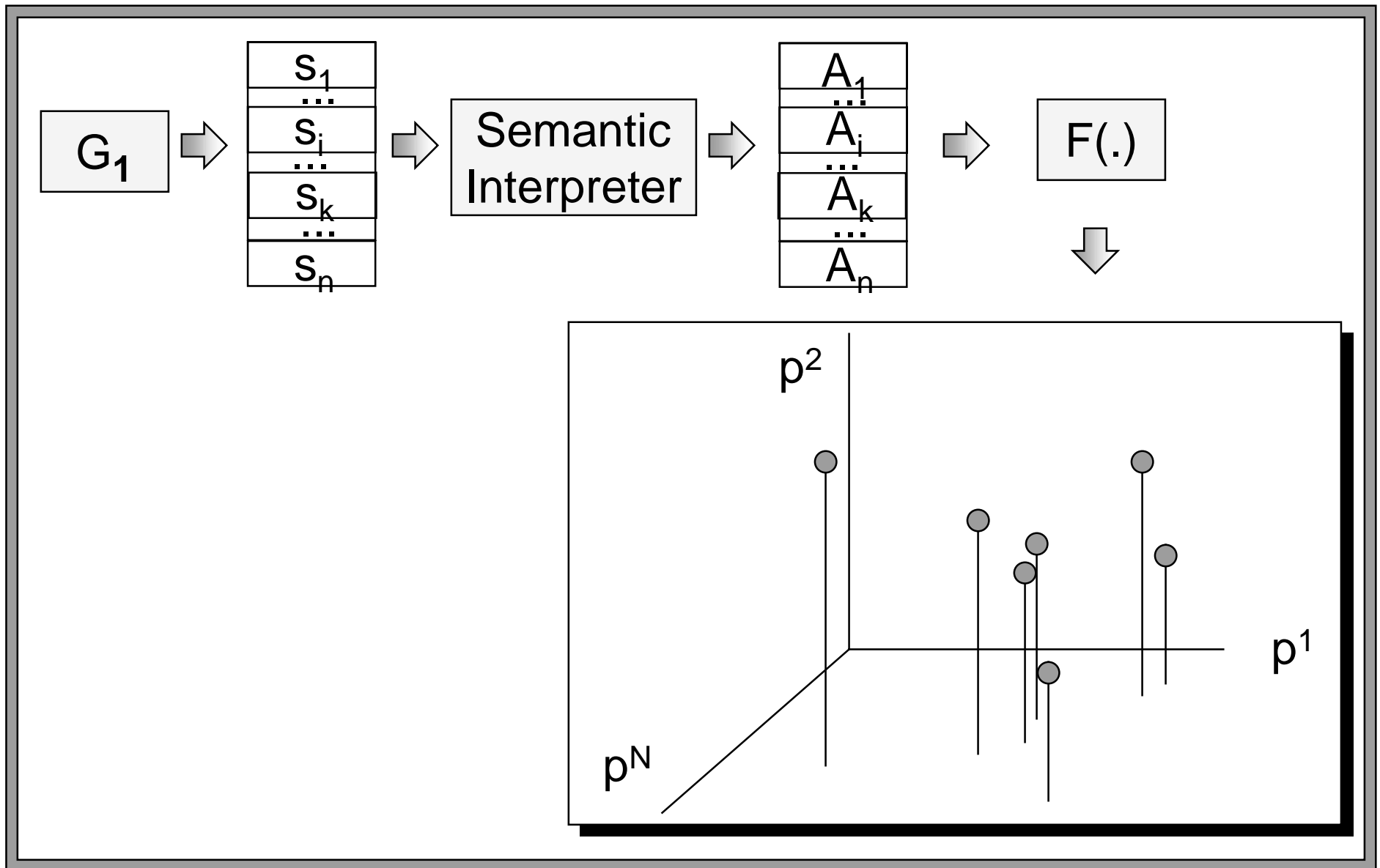
$$\text{X Or Y} = \text{Max (X, Y)}$$

$$\text{Not (X)} = 1 - X$$

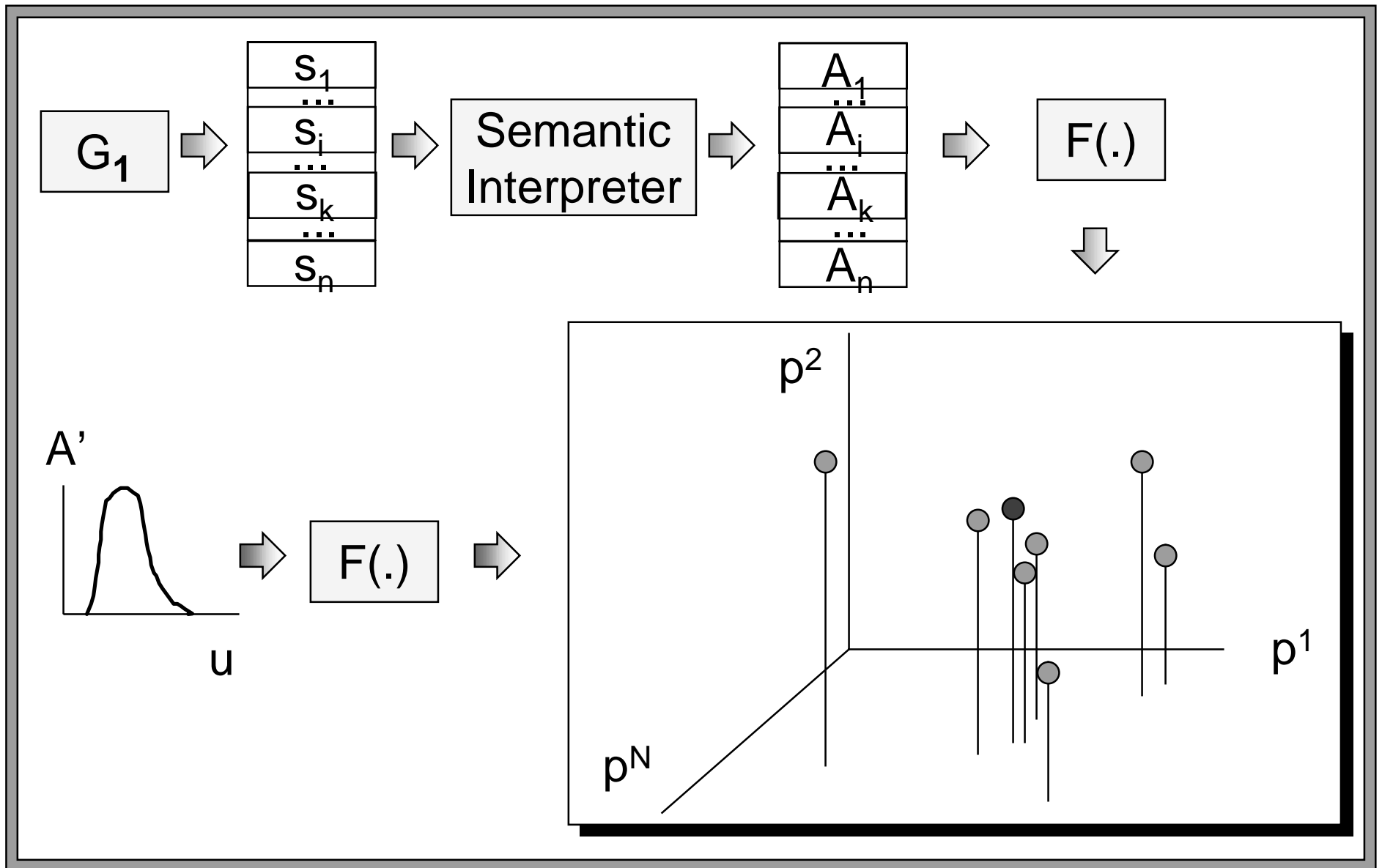
# Example (cont)

	d1	d2	dinf
Low - Very Low	0.06	0.10	0.25
Low - More_or_less Low	0.06	0.11	0.25
Low - Sort_of Low	0.21	0.36	1
Low - More_or_less Middle	0.54	0.67	1
Low - Middle	0.49	0.63	1
Low - High	0.55	0.66	1
Low - Very High	0.49	0.61	1
Very Low - Very High	0.43	0.58	1

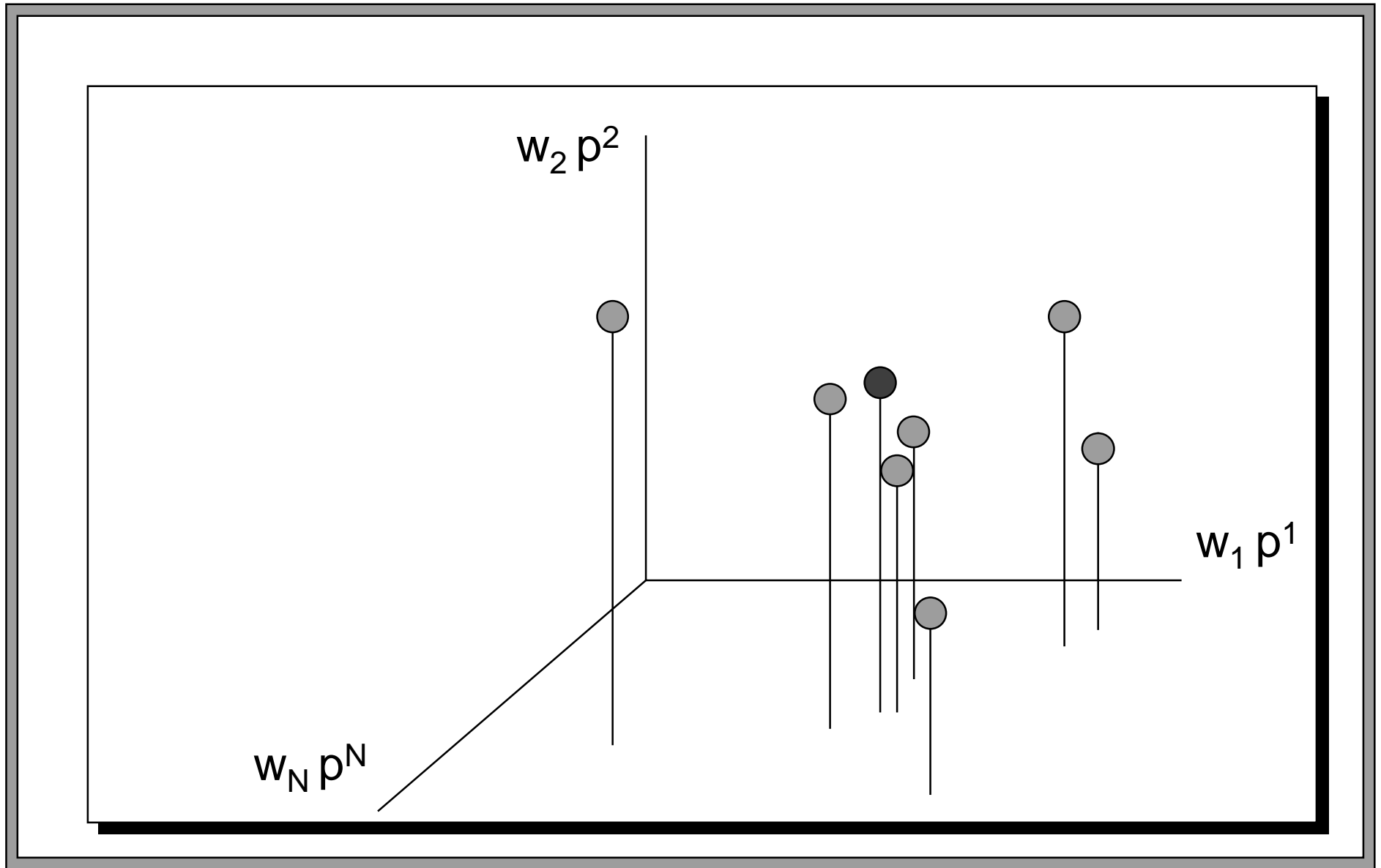
# The Engineering Solution: PR Approach (1)



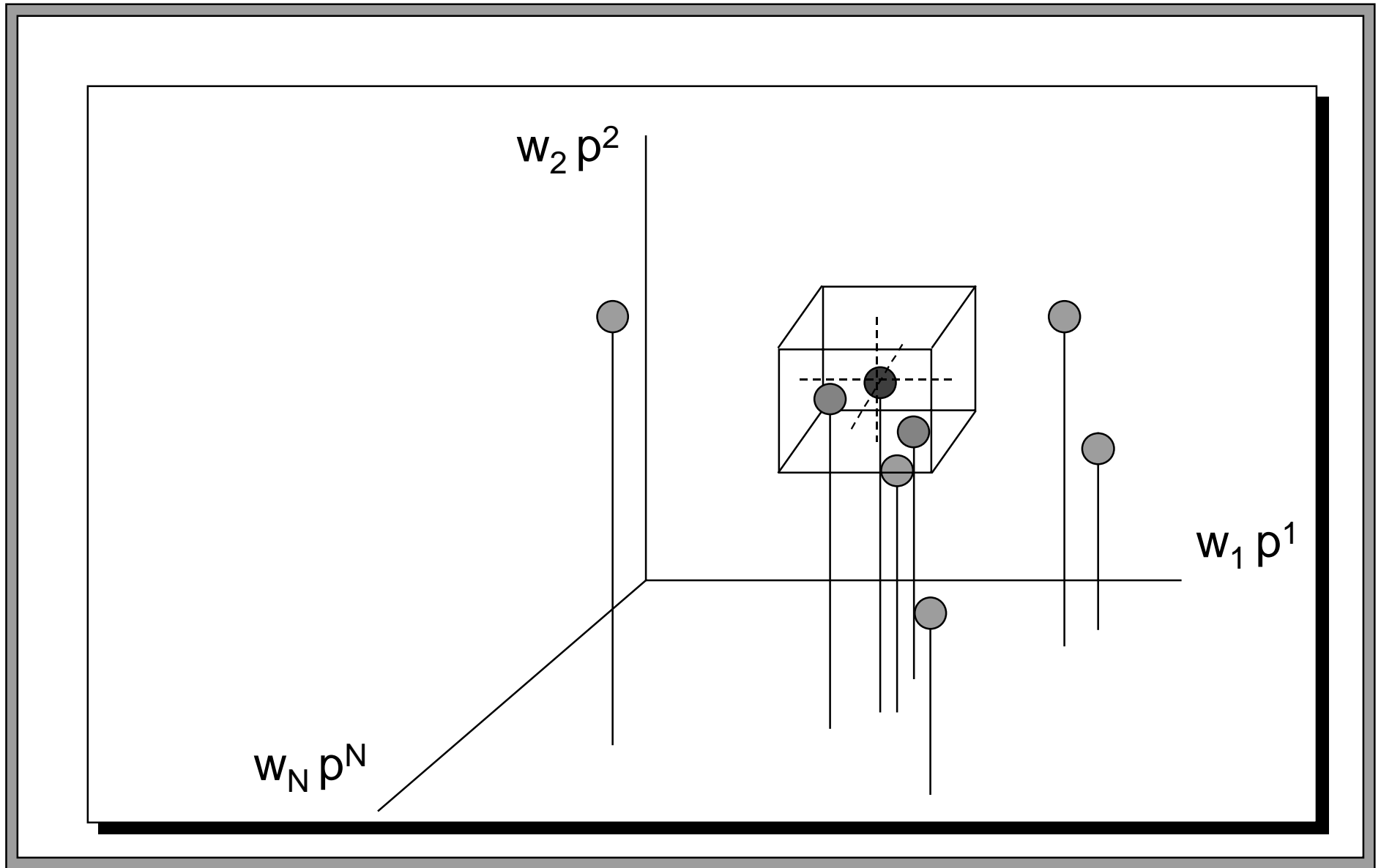
# The Engineering Solution: PR Approach (2)



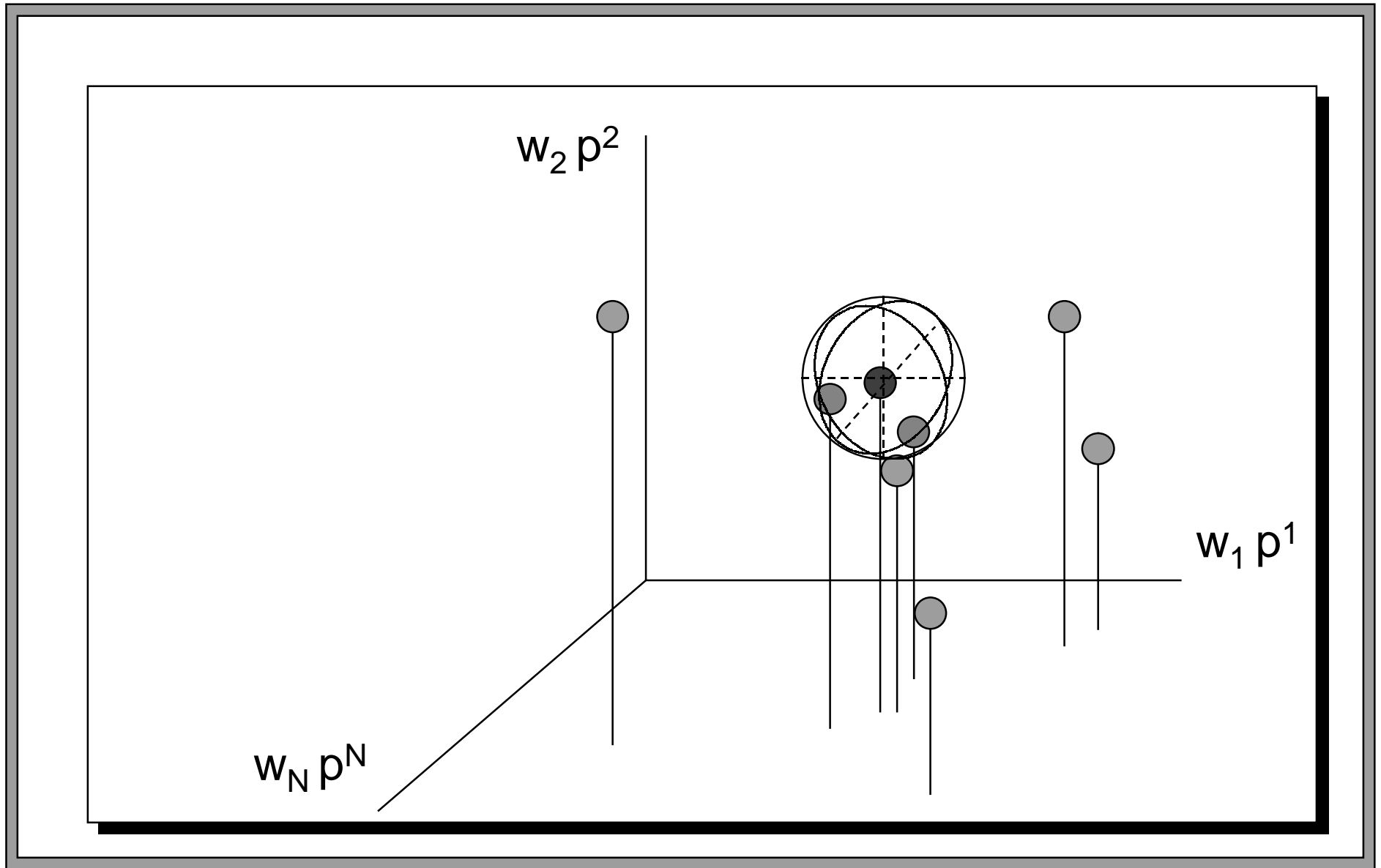
# The Engineering Solution: PR Approach (3)



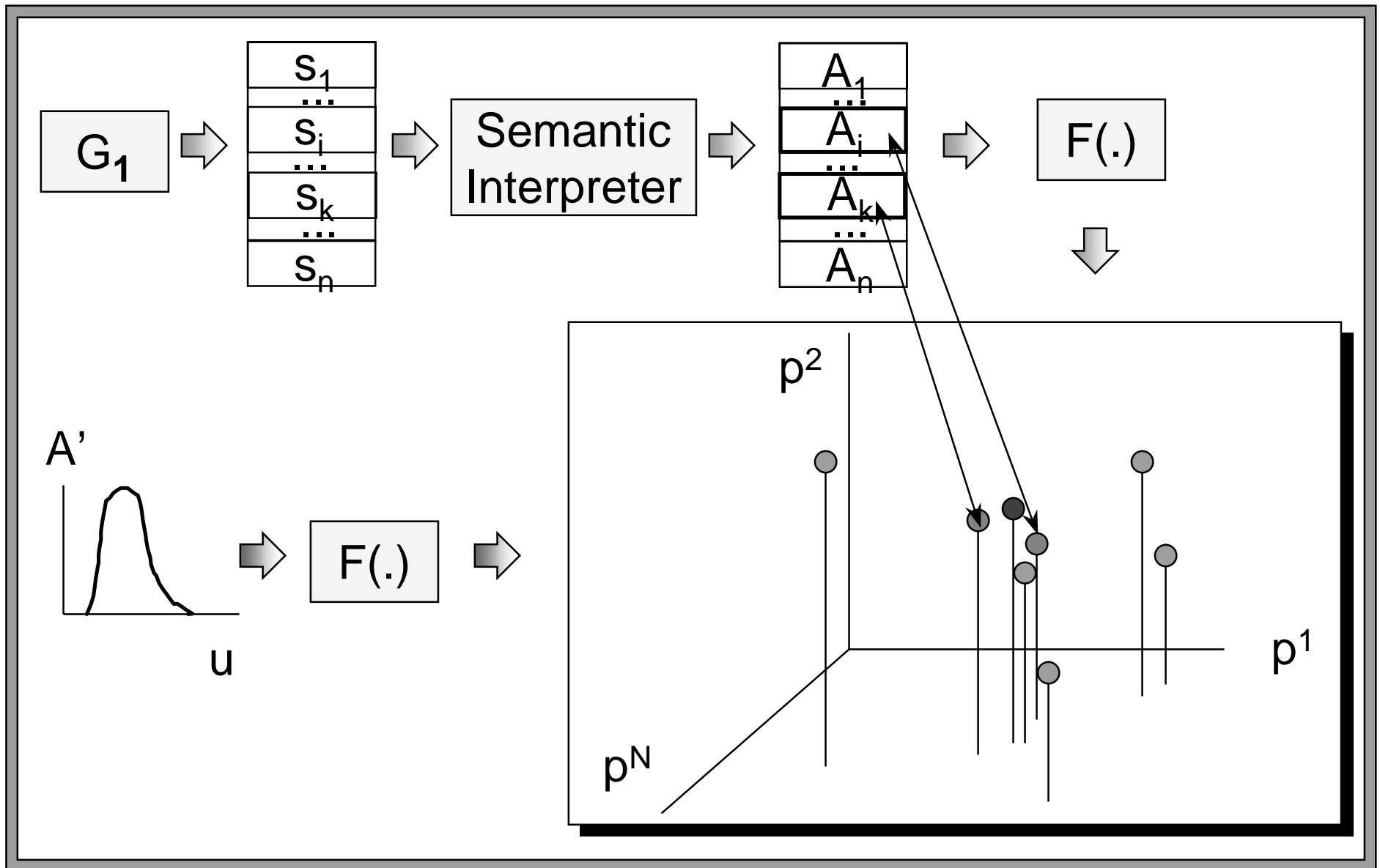
# The Engineering Solution: PR Approach (4)



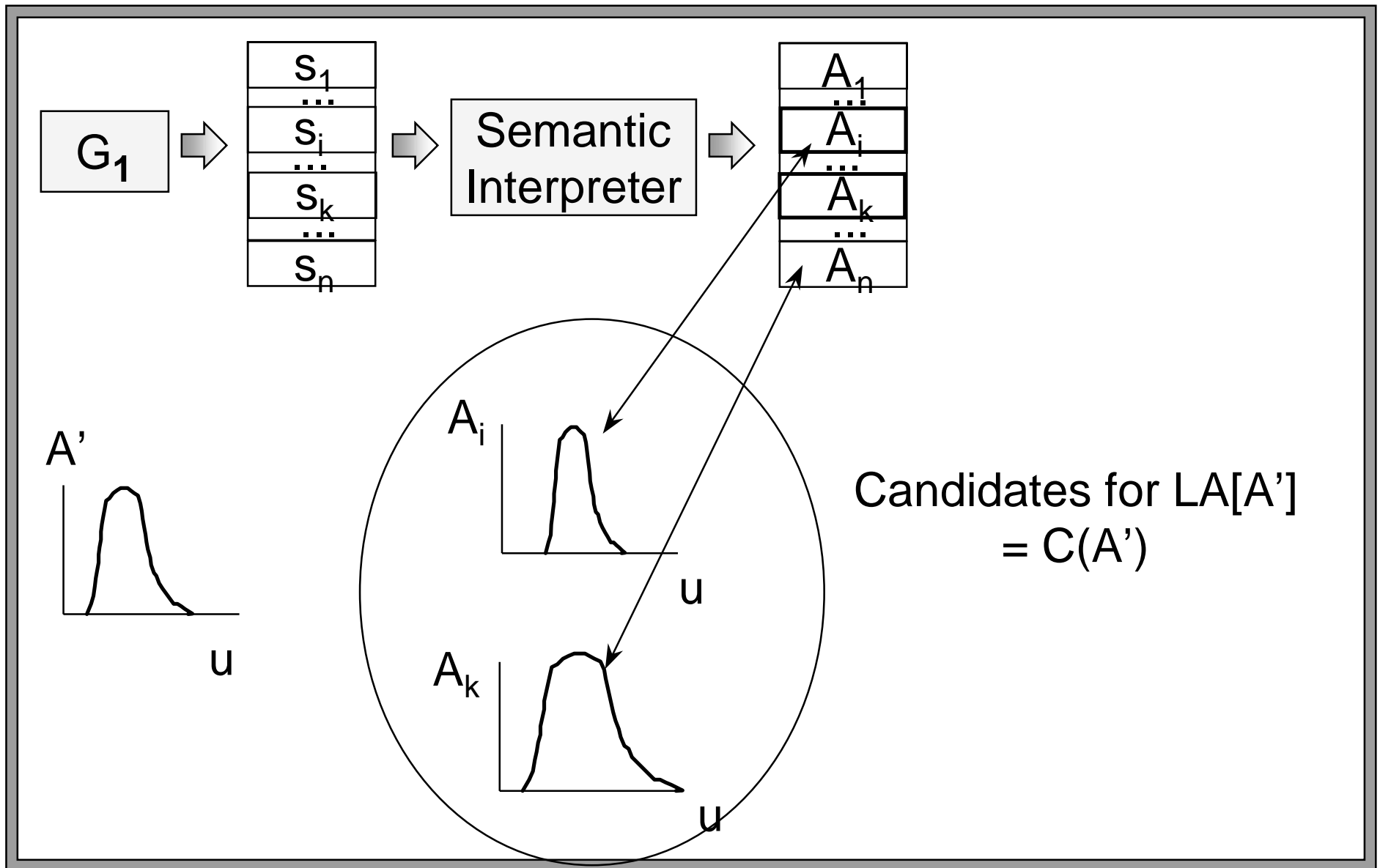
# The Engineering Solution: PR Approach (4')



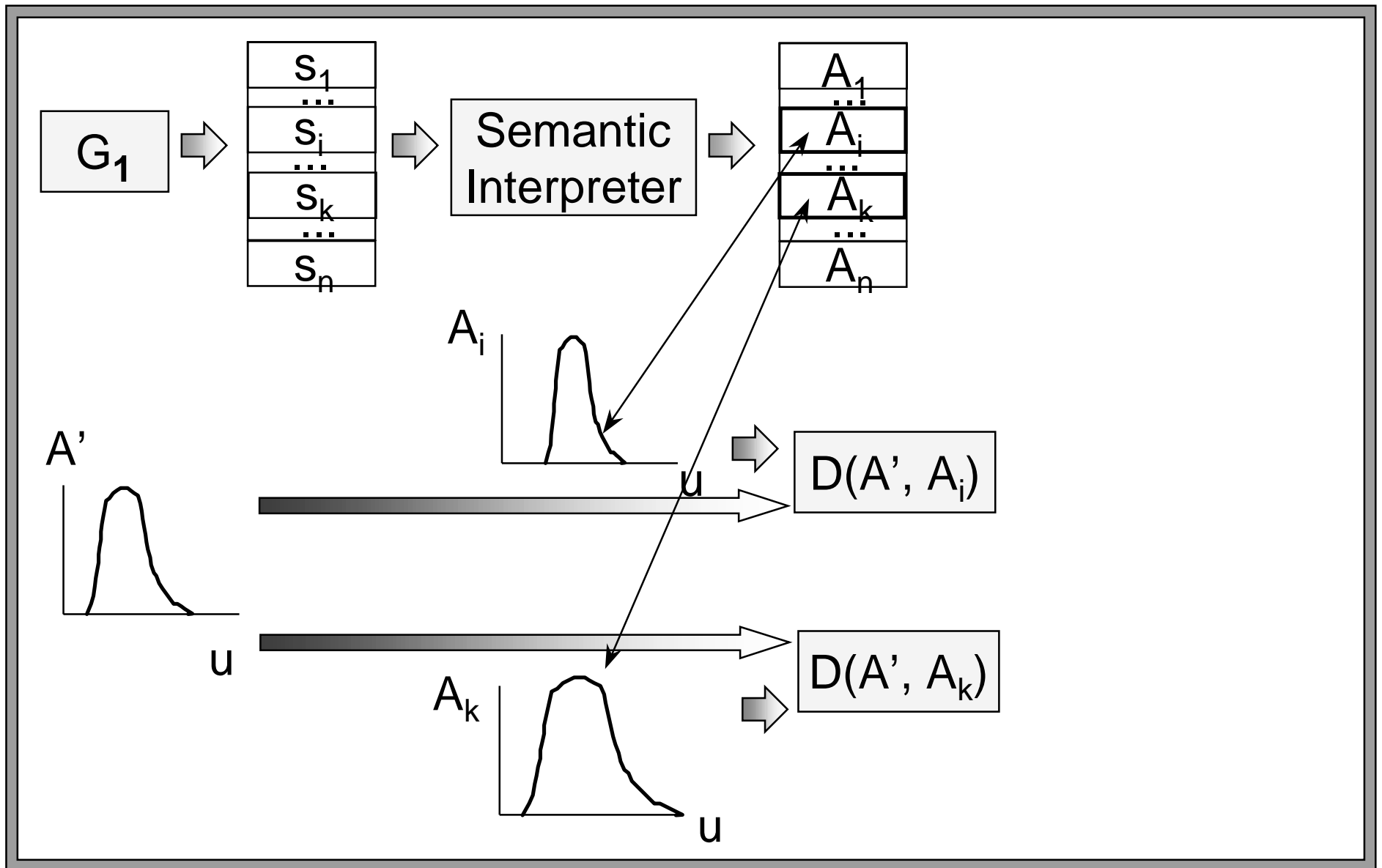
# The Engineering Solution: PR Approach (5)



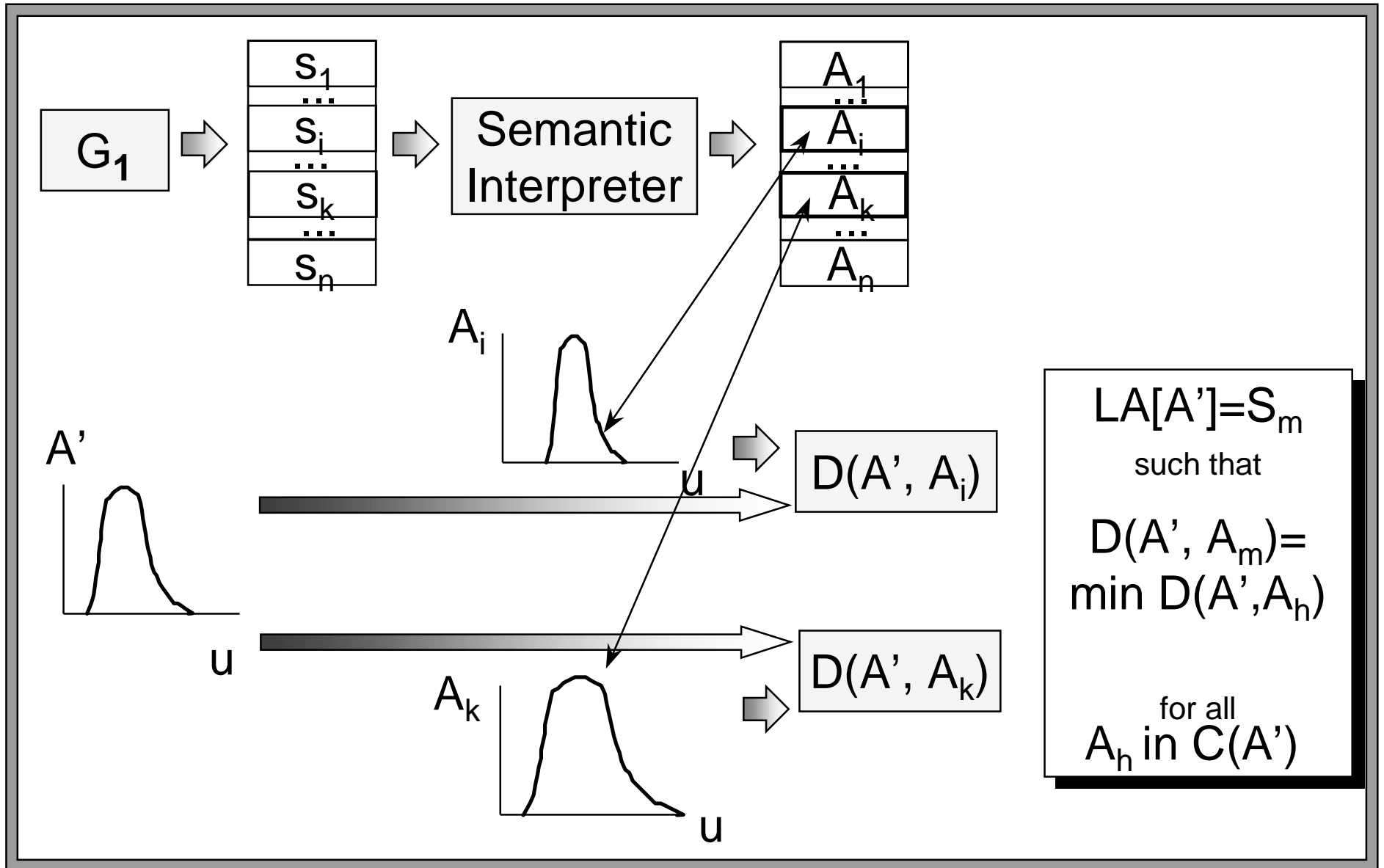
# The Engineering Solution: PR Approach (6)



# The Engineering Solution: PR Approach (7)



# The Engineering Solution: PR Approach (8)



# Feature Extraction and Classification

- Starting from the assumption that the target language is finite:

$$|L(G_1)| = n < \infty$$

- and that the universe of discourse  $U$  is sampled into  $D$  points, i.e.  $|U| = D$
- we define a mapping  $F$ :

$$F: [0,1]^D \rightarrow R^N, \text{ where } N \ll D$$

# Feature Extraction (cont.)

- $F$  maps any fuzzy set  $A_i(u)$  into the  $N$  dimensional feature space  $P$
- Each element in  $P$  is a point (denoted by the vector  $\vec{P}_i$  corresponding to the values of the features of the membership function  $A_i(u)$ )

$$F(A_i(u)) = \vec{P}_i = (p_i^1, p_i^2, \dots, p_i^N)$$

- After several experiments we decided to use the following four features (i.e.,  $N = 4$ ):

# Features Selection

- Sigma Cardinality (Power)

$$p_i^1(A_i) = \sum_{k=1}^D A_i(u_k)$$

- Measure of Fuzziness

$$p_i^2(A_i) = \left\| H(A_i(u_k)) \right\|_2 = \sum_{k=1}^D \left[ H^2(A_i(u_k)) \right]^{0.5}$$

where:

$$H(x) = \begin{cases} x & \text{if } x < 0.5 \\ (1-x) & \text{if } x \geq 0.5 \end{cases}$$

# Features Selection

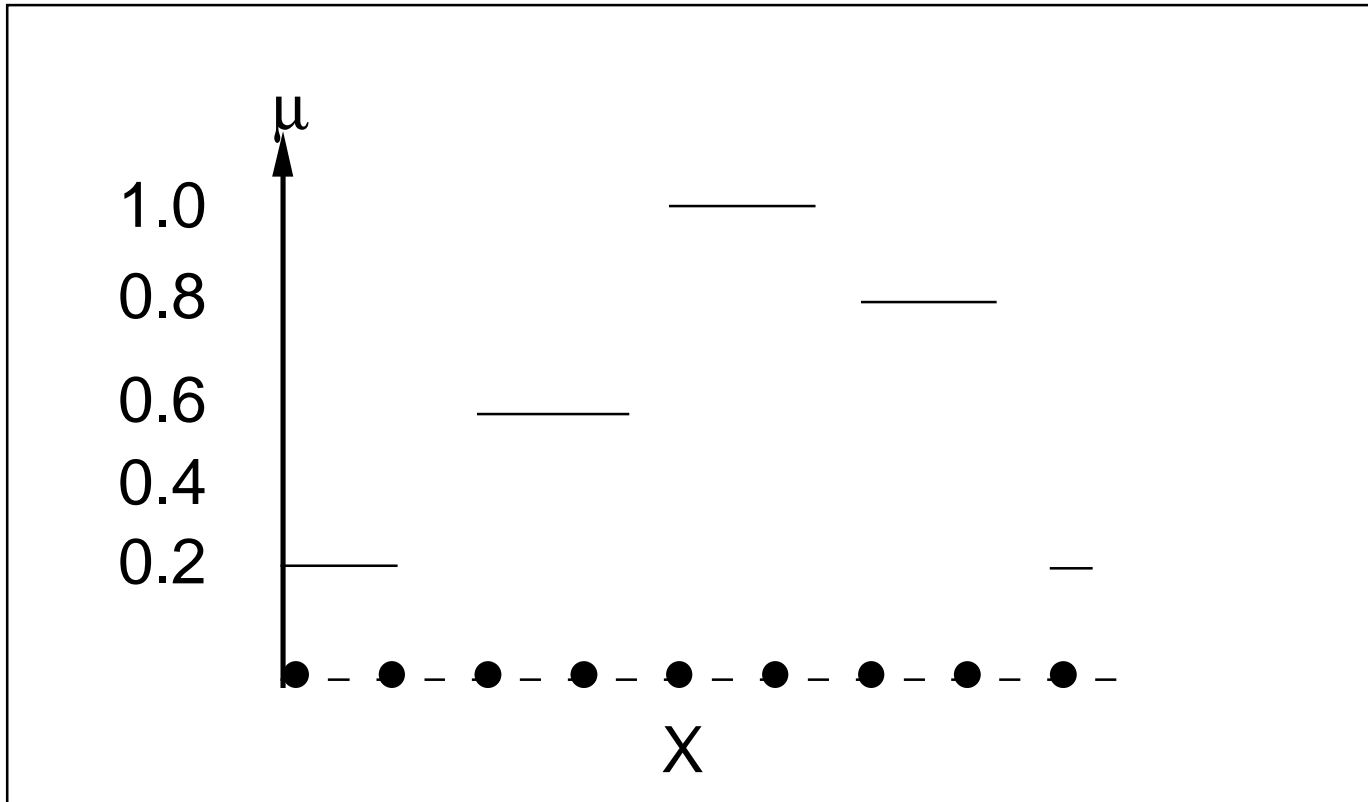
- First Moment (Center of Gravity)

$$p_i^3(A_i) = \hat{u} = \frac{\sum_{k=1}^D u_k \times A_i(u_k)}{\sum_{k=1}^D A_i(u_k)} = \sum_{k=1}^D u_k \times \frac{A_i(u_k)}{p_i^1(A_i)}$$

- Third Moment (Skewness)

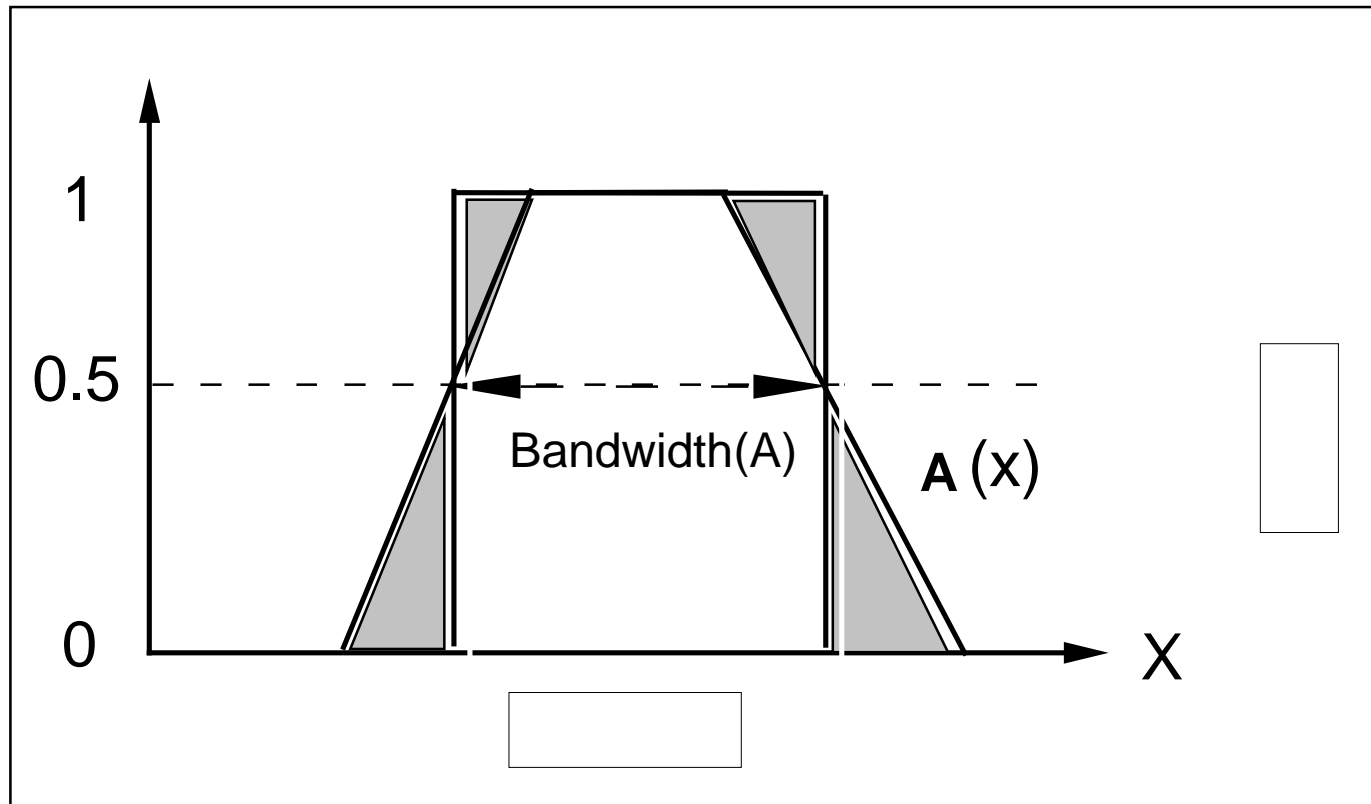
$$p_i^4(A_i) = \frac{\sum_{k=1}^D (u_k - \hat{u})^3 \times A_i(u_k)}{\sum_{k=1}^D A_i(u_k)} = \sum_{k=1}^D (u_k - \hat{u})^3 \times \frac{A_i(u_k)}{p_i^1(A_i)}$$

# Sigma Cardinality



$$\Sigma \text{ Count (A)} = \text{Card(A)} = 5.4$$

# Measure of Fuzziness



**Measure of Fuzziness = Cardinality  $\{|\text{Bandwidth}(A) - A(x)|\}$**   
**= Cardinality  $\{\square\} = \|\square\|_1$**   
**OR**  
**=  $\|\square\|_2$**

# Classification:

- Distances in Weighted Features Space

$$d \left( \vec{P}_{A'}, \vec{P}_{A_i} \right) = \left[ \sum_{k=1}^N \left( w_k (P_{A'}^k - P_{A_i}^k) \right)^2 \right]^{0.5}$$

- Screening of candidates

$$d_2 \left( \vec{P}_{A'}, \vec{P}_{A_i} \right) < \varepsilon$$

(A hypersphere in  $P^N$  of radius  $\varepsilon$ )

# Classification:

- Distance in Membership Distributions Space

$$d_B(f_1(u_k), f_2(u_k)) = -\ln[R]$$

← not a metric

$$d_C(f_1(u_k), f_2(u_k)) = [1 - R]^{0.5}$$

where  $R$  is the *Bhattacharyya Coefficient*

$$R[f_1(u_k), f_2(u_k)] = \sum_{k=1}^D [f_1(u_k) \times f_2(u_k)]^{0.5}$$

and

$$f_j(u_k) = \frac{A_j(u_k)}{\sum_{k=1}^D A_j(u_k)}$$

for  $j = 1, 2$

# Classification:

- The membership functions have been normalized to have its area equal to one

$$f_j(u_k) = \frac{A_j(u_k)}{\sum_{k=1}^D A_j(u_k)} \rightarrow \sum_{k=1}^D f_j(u_k) = 1$$

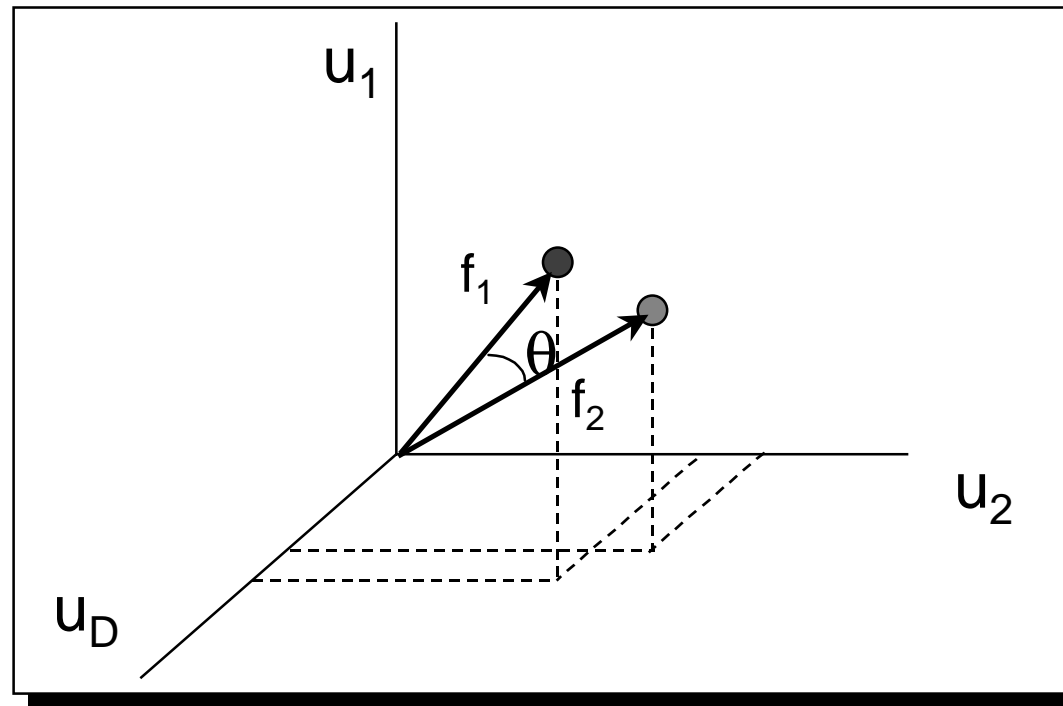
- Geometric Interpretation: Let

$$\sqrt{f_j(u_k)} \quad \text{for } j = 1, 2 \quad \text{and } \forall u_k \in U$$

be the direction cosine on  $j^{\text{th}}$  dimension of two vectors in  $U$  (where  $|U| = D$ ) - The sum of their square equals 1

# Classification:

- *Then the Bhattacharyya Coefficient  $R$  is the cosine of the angle formed by the two vectors*



when  $f_1 = f_2$ ,  $\theta = 0^\circ$ , and  $R = \cos \theta = 1$ , thus  $d_c(f_1, f_2) = 0$

# Weights Determination (Saaty)

- Each Weight  $w_i$  is the ratio:

$$w_i = \frac{I_i}{Range_i}$$

where:

$$Range_i = (\max_{k=1}^n p_k^i) - (\min_{k=1}^n p_k^i)$$

$I_i$  = Importance of feature  $p_i$

Saaty's method is used to elicit  $I_i$

# Reformulation for Parametrized Membership Funct.

- If the membership of the unlabelled fuzzy set  $A'(u)$  is defined by the 4-tuple  $(a', b', \alpha', \beta')$
- and if the semantics of each sentence  $S_i$  in the finite target language  $L(G_1)$ , is represented by a similar 4-tuple  $(a_i, b_i, \alpha_i, \beta_i)$ ,
- then we could define:

$$LA[A'] = S_j \in L(G_1) \text{ such that } D(A', A_j) = \text{Min}_{i=1}^n \{D(A', A_i)\}$$

where:

$$D(A', A_i) = w_1 (|a' - a_i| + |b' - b_i|) + w_2 (|\alpha' - \alpha_i| + |\beta' - \beta_i|)$$

# Reformulation for Parametrized Membership Funct. (cont.)

- *Distance*
  - $d$  could be another similar metric (e.g. a Weighted Euclidean instead of a Weighted Hamming Distance)
- *Weights*
  - $w_1$  and  $w_2$  represent the weights for matching the core and support, respectively:
    - $w_1$  weighs mostly the location of the set (determined by the placement of the core)
    - $w_2$  weighs mostly the spread of the set (determined by the placement of the support)

# LA Applications (1)

## 1) Infinite Language -> Finite Language

– Approximate an infinite language  $L(G_0)$ , generated by a grammar  $G_0$  containing recursive non-terminals, with a finite language  $L(G_1)$

- The term represented by a sentence in  $L(G_0)$  is treated as an unlabelled term. The sentence could be arbitrarily long and therefore difficult to understand
- Design a grammar  $G_1$  generating a finite language  $L(G_1)$  that provides sufficient coverage of the element of discourse (descriptors)
- Select the sentence from from  $L(G_1)$  with the closest meaning

# LA Applications (2)

## 2) Interpretation of results from AR processes

– Given:

$$R = \bigcup_{i=1}^n R_i = \bigcup_{i=1}^n (\vec{X}_i \rightarrow Y_i)$$

– We may provide a linguistic answer to the question:

If  $(\vec{X} \text{ is } \vec{X}')$  then what is the output  $Y'$

– which is:

$$LA[\vec{X}' \bullet R]$$

# LA Applications (3)

## 3) Interpretation of Truth Qualification Results

– Given the Possibility Function:

$$(X \text{ is } F) \rightarrow \prod_x = F$$

– Then, its Truth Qualification

$$(X \text{ is } F) \text{ is } \tau \rightarrow \prod_x = F^*$$

- $F$  and  $F^*$  are fuzzy sets in  $U$ ,  $\tau$  is a fuzzy set in  $[0,1]$
- $F^*(u) = \tau( F(u) )$  – using the extension principle
- The interpretation is:  $LA[ F^*(u) ]$

# LA Applications (4)

## 4) Interpretation of Extension Principle Results

– Given the mapping:

$$* : U \times V \rightarrow W \quad \text{and} \quad A \subseteq U, B \subseteq V$$

– Then the result of applying the mapping  $*$  to  $A$  and  $B$  can be interpreted as:

$$A * B = LA \left[ \text{Sup}_{w=u*v} \text{Min}(A(u), B(v)) \right]$$

# LA Applications (5)

## 5) Interpretation of Results of a Syntactic Substitution Process

- See Riddle example