Section 1. Problem:
Multi-view subspace clustering aims to partition a set of unlabeled multi-source data into their underlying groups.

- Many works prefer to learn a common representation, ignoring the complementary information between different views.
- Existing works tend to execute the subspace learning and spectral clustering in two separated steps, without consideration of the fact that these two steps highly depend on each other.

Contributions:
To overcome the above shortcomings, we propose a novel multi-view clustering algorithm namely ECMSC.

- A novel position-aware exclusivity term is proposed to effectively exploit the complementary information between different representations.
- An indicator consistent term is employed to advocate the label consistency among the complementary representations.

Section 2. Our Method (ECMSC):
Compared to the value-aware Hilbert-Schmidt Independence Criterion (HSIC) [2], we introduce a novel position-aware exclusivity term, which can effectively avoid the scale issue of element values in different representations. Moreover, an indicator consistency term is proposed to unify the processing of subspace clustering.

Definition:
- **Exclusivity**: Exclusivity between two matrix $U \in \mathbb{R}^{n \times m}$ and $V \in \mathbb{R}^{r \times m}$ is defined as $\mathcal{X}(U, V) = \|U \odot V\|_1 = \sum_{i,j} (u_{ij}, v_{ij} \neq 0)$, where $\odot$ denotes the Hadamard product (i.e., element-wise product).
- **Consistency**: Consistency of indicators into one framework:

The Objective Function:
To consider the exclusivity of different representations and the consistency of indicators into one framework:

$$\min_{X_1, X_2, \ldots, X_N} \sum_{i=1}^{N} \lambda_i \|Z_{i} \odot \Theta_i\|_1 + \lambda_{consistency} \sum_{i=1}^{N} \|Z_{i} \odot \Theta_i\|_1 + \lambda_{exclusivity} \sum_{i,j} (u_{ij}, v_{ij} \neq 0).$$

Algorithm:
We propose a solution by solving the two sub-problems alternatively:
- Given $F$, compute each exclusive representation $Z_i$ and the corresponding residual $E_i$ by ADMM algorithm.
- Given $Z_i$ and $E_i$, find the consistent indicator $F$ by spectral clustering.

Parameters Effects:
Inspired by previous works [25, 18], we set $\alpha_1 = \eta^{-1}$ and $\alpha_2 = \lambda_1 \beta_{in}$, where $\eta = 1, 2, \ldots, \tau$ is the iteration index. $\alpha$ is to control the representation exclusivity term, $\beta$ is to balance the indicator consistency term.

Section 3. Experiments:
- **Given a set of unlabeled data with multi-view features, the ECMSC algorithm will directly output the clustering results.**
- **Extended Yale-B Results:**

<table>
<thead>
<tr>
<th>Method</th>
<th>NMI</th>
<th>ACC</th>
<th>ARI</th>
<th>F-score</th>
<th>Precision</th>
<th>Recall</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single</td>
<td>0.760</td>
<td>0.760</td>
<td>0.760</td>
<td>0.760</td>
<td>0.760</td>
<td>0.760</td>
<td>0.760</td>
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<tr>
<td>Multiple</td>
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<td>0.750</td>
<td>0.750</td>
<td>0.750</td>
<td>0.750</td>
<td>0.750</td>
<td>0.750</td>
</tr>
</tbody>
</table>

| Proposed | 0.740 | 0.740 | 0.740 | 0.740 | 0.740 | 0.740 | 0.740 |

**Parameters Effects:**
- **From left to right**: The columns are visualization of subspace representations $Z_i$, $Z_j$, and the indicator matrix $\Theta_i$.
- **From top to bottom**: The rows are the results of ECMSC$_{avg}(ACC=0.701)$, ECMSC$_{Agg}(ACC=0.689)$ and ECMSC(ACC=0.781), respectively.