The case of modern AI in Credit Markets

In the following, AI means modern deep (reinforcement) learning (DRL). The term AI excludes classic (statistical) ML techniques (e.g. Lasso, Ridge, SVM, Random Forest, Gradient Boosting etc).

What distinguishes modern AI compared to classic statistical ML:

1. Handling unstructured data:
   1. Images
   2. Text
   3. Complex structures (e.g. Graphs)
2. Representation learning
   1. Still not very well established for tabular data
   2. Allows for interactions between features (two interacted weakly features may lead to a strong signal)
3. Sequential/Temporal modeling
   1. The family of RNNs
   2. transformers
4. Data generation
   1. Especially unstructured data
5. Handling non IID data
   1. Graph Neural Networks (GNNs)
6. Multi-modality:
   1. Text and images together
7. Algorithmic decision making
   1. Through multi-armed bandits and RL

What characterizes data in the credit space:

1. There is an unstructured component:
   1. News
   2. Filings
   3. Chats/communications
2. Hierarchical (multi-level)
3. Temporal
4. Non-stationary
   1. Over time
   2. Across data points (data is NOT IID)
5. Censored information (unavailable information, missing)
   1. Non trading securities don’t have a reliable “price”
6. Low SNR
7. Data can be thin (we don’t have very large data sets)

The credit market is an adaptive dynamic complex(\*) system with feedback, which makes it ideal for stochastic optimal control & algorithmic decision making modeling.

In addition, data is both:

1. sourced from third party vendors and
2. proprietary persisted in internal data stores

Based on the above, it appears that modern AI can rescue shallow statistical ML on modeling challenging credit market data characteristics such as:

1. Temporal : the likes of transformers
2. Multi-level and Not iid : the likes of GNN
3. Censored information: the likes of generative AI
4. Data augmentation: the likes of generative AI

Therefore, it seems reasonable to classify the use cases into:

1. Foundational use cases: essentially, we would leverage modern AI techniques in existing (or future) models to account for the limitations of shallow statistical ML methods
2. Applied use cases: basically, this aims at providing tools to be used directly by producers (traders and sales) or management and can be classified into:
   1. Querying Existing information: for example
      1. A chat bot traders can interact with to pull information otherwise only available through DB queries or scripting
   2. Focus attention on relevant (happening-now) information: for example
      1. Listening to Edgar SEC and summarizing new filings
   3. Automation: for example
      1. Auto quoting and responding of rfqs
      2. Automatic list sending and acting on received responses

An alternative classification could be:

1. operation optimization (cost reduction, time saving, etc)
2. Edge amplification (PnL improvement)

It does seem that both foundational and applied use cases would benefit significantly from building a multi-modal foundation model for credit (or even for the whole firm) that:

1. Combines both unstructured and tabular data
   1. Maybe turn tabular data to unstructured somehow
2. Combines both third-party and proprietary data sets
3. Fine-tunable to address specific tasks
   1. Traders
   2. Sales
   3. Management

A potential execution roadmap could be:

1. Start with an open source LLM
2. Gather & prepare relevant credit data
   1. If tabular , unstructure it
3. Transfer learn (a bit more than finetuning the output layer) on the open source LLM to produce the multi-modal foundation model (MMF)
4. Spawn fine-tuned foundation models to specific tasks
   1. For handling clients
   2. Sec filing
   3. News
   4. Reporting for management

(\*) complex as in the whole does not equal its components (not as complicated). A concept that stems from complex systems theory