Group 1 - In Person

Opportunities

- AI-based ensemble combined/compared with physics-based deterministic (how to trigger fast growing modes?)
- Land dynamics representation
- Ocean model simulation and downscaling
- Physics parameterization
- Observation impact (e.g. FSOI) diagnostics
- Fast adjoint model for 4DVar
- Rapid turnaround of output for making implementation decisions
- Basis for large-ensemble particle filters
- Fine tuning of models originally trained on reanalysis
- Toward continuous training

Barriers

- Broader access to training datasets
- Realistic error growth in DLNWP ensemble across time scales.
- Time resolution of ML models (need to be similar to physical models)
- Vertical levels for satellite observation operators
- Where are my GPUs/TPUs?
- Observation data ingest in the cloud
- Address concerns of customers/users/forecasters (participate in testbed evaluation, involve social scientists)

Group 2 - In Person

Opportunities

- Post Processing (e.g. generate better reforecast training datasets)
- Downscaling and Nowcasting
- Large community development projects (multiple institution) towards an end-to-end system
- weighted average from multiple ensemble forecasts (dynamical and data driven). Add AI to the NBM.
- Opportunity to overcome institutional bias by running ML forecasts in parallel to traditional guidance and making them available in ways that forecasters are used to use it.
- extremely large ensemble forecast for MWR or for DA.
- Faster CI/CD and R2O process (esp retrospectives)

Barriers

- need to design systematic way to do evaluations that is consistent with how testbeds and forecasters use forecasts.
- It might be cost prohibitive to train models at CAM scales
- need extension to the rest of the modeling suite (aerosol, ocean..)
- Alternative ways to get AI into operations (e.g. bypass hardware procurement bottlenecks).
- NCO barriers for onboarding libraries and software.
- Inhouse talent and expertise to optimize, re-train, and maintain models.
- Infrastructure support for MLops.
- Cultural and financial barriers for attracting top talent in the federal pipeline.
- Access to GPUs/TPUs

Group 2 - In Person

Opportunities

- Formulate grand forecasting challenges for AI to solve (e.g. MJO traversing maritime continent, freezing rain,...)
- Train ensemble of models towards specific cost objectives (e.g. TC, fireweather, winter weather?). we no longer need single model that can do it all.
- Obs operators with AI
- User-driven ensemble sensitivity tools.

Barriers

- The way forecasters learn and work can match fast pace of technology development, Forecasters will come along if we can demonstrate improved skill for metrics relevant to forecasters.
- Develop SOPs for forecasters so they can do their job better.
- Availability of extra diagnostic fields (e.g. CAPE)
- Reforecasts with AI model. DO they have to be out of training sample?
- Models are developing too rapidly
- Large ensembles will need visualisation/clustering tools. Develop SOPs for forecasters so they can do their job better.
- How to do hybrid compute CPU+GPU

Group 3 - In Person

Opportunities

- Targeted/hybrid use of ML in current NWP systems
    - obs processing, forward operators, physics
- CAM scale emulation
    - Leverage 404 WRF reanalysis for training
- Global scale emulation
    - ERA5 or GEFS v12
    - Accelerate new 40-year reanalysis developed for SFS
- Public/private partnerships
    - Follow on successful OTAs/CRADAs of the past, even contracts
    - Other pathways for knowledge/staff exchange

Barriers

- Development is easy, transition is hard
    - testing, evaluation, testing, evaluation, training, expertise for 24/7 support, system architectures/supported tools (is NWS positioned?)
    - Architecture compatibility between current models and ML (GPU vs CPU)
- Generalized models- do we need climate projections in training to capture extremes?
- Dense observing system non-existent. What is sufficient?
- Need focused, collaborative efforts with clear operational objectives

Group 4 - In Person

Opportunities

- Low hanging fruit – feed ML into existing streams and start evaluating in parallel.
- Leverage testbeds as soon as possible to get forecasters/customers looking at things, identify the starting point.
- Use this as opportunity to break out of old ways of doing things – accelerate innovation and T2O.
- Focusing on datasets that do not already exist to bring partners to the table (convective scale reanalysis, for example).
- Efficiencies – both in operational production but also freeing up development cycles.

Barriers

- Risk aversion of customers. Institutional / cultural barriers (need NCO at meetings like this). Fear of the unknown.
- Computing – lack of GPU infrastructure
- Cost of getting into this field – there are trade-offs that have to be made (e.g. focus more on generating datasets, less on traditional development activities)
- Things are moving extremely fast – need to be flexible. Cannot lock ourselves into old technology.

Group 1 - Remote

Opportunities

- Few months: Fine tune one or more of these models on GFS initial conditions, develop metrics, start evaluating in testbeds with forecasters.
- 1-3 yrs: Ensembles for more appropriate spread/skill metrics. EC: Strong likelihood of success
- 5 years: Explore AI for DA. Lots of complex components of the DA framework
- AI helps NOAA gain more diversity in modeling suite as UFS consolidation reduces diversity
- Culture: Opportunity and barrier. Opportunity to accelerate our R2O process
- AI can do 3 year retrospectives in 1 day. Facilitates rapid testing and evaluation
- AI for post processing still is a huge opportunity to support forecasters.
- Continue existing AI efforts: CRTM, bias correction
- Language models for science communications
- Empower staff to learn - MOOC for ML

Barriers

- Graphcast, Pangu were 1-2 years in development. Need to make the R2O2R pipeline faster to keep pace. Science is moving faster than we are comfortable with
- GPUs and HPC (budget, availability, understanding)
    - There are programs soliciting proposals for GPU time
    - Training and spin up on using GPUs
- Organizational stovepipes - can we work across Labs/LOs?
- Skills gaps. Need a combination of hiring and training
    - At ECMWF, staff were excited to learn AI/ML
- Having ML/AI-ready data hosted on the cloud (w/ metadata). Additional QC currently often needed
- Open code/science when industry is leading (each company has different motivations)
    - Counterpoint: Academia is building LLMs just as fast
- O2R is a challenge, particularly from academia
- Ensuring the quality of AI-based products
- NOAA slow to use Generative AI for software development

Form a tiger team of 3-5 people. Redeploy existing expertise within the organization. Can start small (evaluating current models) and scale up

Group 2 - Remote

Opportunities

- Efficiency
    - The efficiency to generate large ensemble sets, useful for DA, S2S, Forecasts
    - Optimization of every calculation we do from QC of observations, post processing, images, test products
    - AI explicitly to synthesis data and reduce cognitive overload
    - AI knowledge discovery - fast search to find specific events for further analysis and research
- AI can directly go to impact variables, not traditional NWP variables
- Providing meaningful probabilistic data of extreme high impact events
- Explainable
    - Providing training and other opportunities to explain how, why, what of AI
    - Seeing how AI performs alongside traditional physical models

Barriers

- Fear of being replaced
- Partnerships R2O and O2R
    - Require funding and agreements on both sides
- Testbeds
    - Access to real forecasters – they are busy
    - Communicating needs from operations to research
    - More opportunities for forecasters to evaluate products
- Technical barriers
    - Research environment does not match operation environment
    - Access to Data
    - Required to retrofit new tools into existing (sometimes archaic) infrastructure
- Budget
    - Different readiness levels have different funding sources
    - Lack of budget, or prioritization towards AI
    - Agility and speed to quick changes